Developing an integrated information system to assess the operational condition of deep level mine equipment

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Abstract

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Deep gold and platinum mines in South Africa are under pressure to remain profitable. These mines typically operate at depths of more than 2 km below surface. Complex systems are used to supply the underground operations with cold water, compressed air and ventilation. The operational condition of these systems has an impact on the mine's production, as well as the safety of the underground workers. It is therefore vital to avoid any unnecessary operational and capital expenditures.

Equipment maintenance is one area where deep mines can realise financial savings. Research has shown that preventative maintenance is an effective strategy to improve equipment reliability. Maintenance costs can be reduced by preventing breakdowns and by avoiding major repairs. Mines therefore need to consider a condition-based maintenance (CBM) strategy to lower operational costs, reduce the risk of equipment failure and promote underground safety.

CBM can be performed by continuously evaluating the operational condition of equipment. Considering the procurement and installation cost of commercial monitoring systems, the current solutions are not feasible. It is also not feasible to manually inspect or analyse the data of the mine's entire inventory of assets on a regular basis. An innovative methodology was developed to provide maintenance supervisors with information that is summarised and easy to interpret. An automated system, based on the new methodology, was developed to make use of available data and infrastructure to avoid additional capital expenditures.

The information system was implemented on six mining sites. Data from remote servers (located on site) was sent to a centralised server to be processed. Daily exception reports provided multiple stakeholders with information regarding operational risks. An online platform was used to provide users with remote access to the risk notifications. The platform also displayed *live* parameter profiles that were updated every 30 minutes.

Two case studies were compiled to document the measured results. Between these two case studies more than one million data samples were analysed per month. The analysis drastically reduced the time it took to locate unsound equipment behaviour. On average, maintenance personnel only needed to evaluate 6% of the input parameters that were identified as exceptions, or possible risks. Where maintenance was performed, the average number of exceptions was reduced from 61 to 25 during the first month. A further reduction to an average of nine exceptions per month was observed during the following four months.

The information system improved the operational awareness on the mine and within the corporate structure of the mining group's management. The notifications that were generated by the information system, were incorporated into the mine's maintenance strategy. It was concluded that operational costs and risks can be lowered by integrating CBM with the existing scheduled maintenance.

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Nomenclature

ANN	Artificial Neural Network
APN	Access Point Name
BAC	Bulk Air Cooler
CBM	Condition-Based Maintenance
CSV	Comma Separated Values
CT	Computed Tomography
DBMS	Database Management System
DE	Drive End
DNN	Deep Neural Network
DSS	Decision Support System
ERD	Entity Relationship Diagram
ESCO	Energy Services Company
FFT	Fast Fourier Transform
FIS	Fuzzy Inference System
FMEA	Failure Mode and Effects Analysis
GPL	General Public Licence
ISP	Internet Service Provider
KPI	Key Performance Indicator
MHSA	Mine Health and Safety Act
MRI	Magnetic Resonance Imaging
MSE	Mean Square Error
MTBF	Mean Time Between Failures
MTTR	Mean Time To Repair
NDE	Non-Drive End
OOE	Overall Operation Effectiveness
OPC	Open Platform Communications
PK	Primary Key
PLC	Programmable Logic Controller
RCM	Reliability Centred Maintenance
RMS	Root Mean Square
RNN	Recurrent Neural Network

SCADA	Supervisory Control and Data Acquisition
SCRF	Safe Caution Risk and Failure
SIM	Subscriber Identification Module
SMS	Short Message Service
SMTP	Simple Mail Transfer Protocol
SVM	Support Vector Machine
TOU	Time of Use
TPM	Total Productive Maintenance
VPN	Virtual Private Network
VRT	Virgin Rock Temperature

CHAPTER 1

Introduction

1.1 Preface

A typical mining environment consists of harsh physical conditions and complex processes. Deep level mines are constantly increasing their operating depths in search of ore reserves. These deep mines operate at depths of up to 4 km below surface [1]. An enterprise such as this involves large industrial equipment, which is expensive to procure, operate and maintain.

The mining industry in South Africa is under severe pressure to remain profitable [2], [3], [4], [5]. Daily production targets, energy usage considerations and equipment availability all contribute to the operational productivity of the mine [6], [7]. Mines have stringent budget constraints and can therefore especially not afford any avoidable expenses regarding operational and capital expenditures [8], [4].

An efficient maintenance strategy can save a mining group time and money [6]. Being aware of a system deficiency, before it develops into a serious problem, can enable maintenance personnel to service the piece of equipment and avoid a critical failure [9]. This reduces the repair cost, requires fewer resources and reduces downtime [10]. A proactive approach does, however, require that machine- and process data is constantly analysed.

A number of key parameters are indicated on a pump diagram, shown in Figure 1.1. These are only some of the measurements that are available for a single pump. A vast number of measurements are available when considering an entire mining operation. Figure 1.2 shows a simplified example of a deep level mine layout. This demonstrates the size of a mining operation, as well as the locations of the different types of equipment.

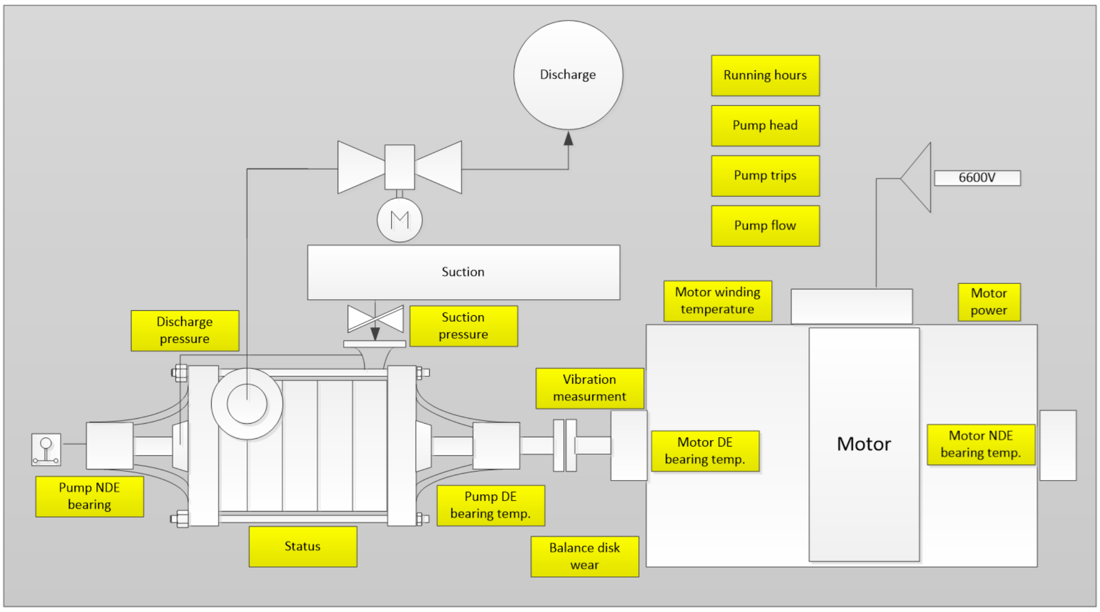


Figure 1.1: *Pump monitoring parameters*

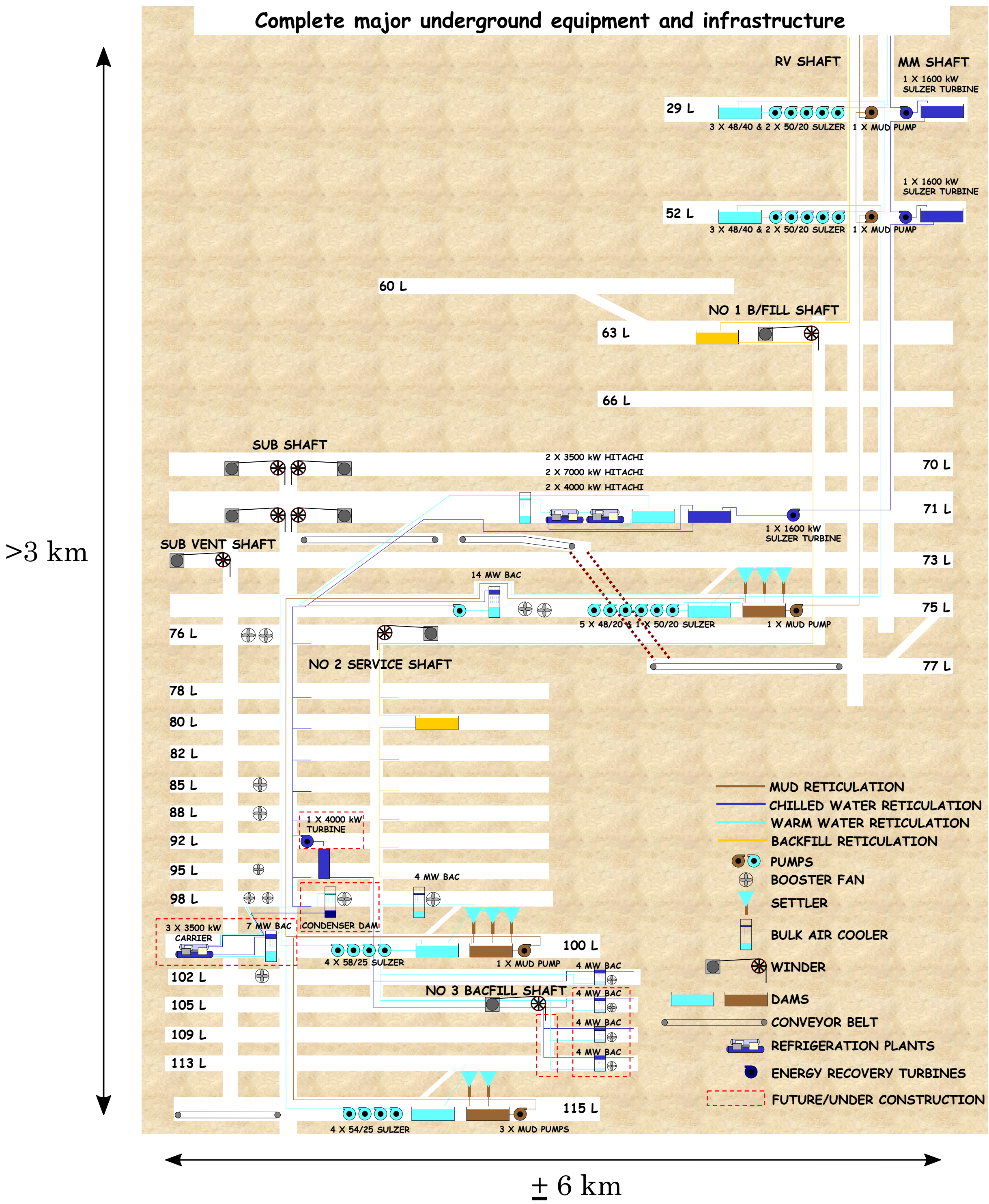


Figure 1.2: *Simplified deep level mine layout*

1.2 Background on mining systems and operations

Various systems are used on a daily basis for different types of mining operations. These systems include water reticulation, compressed air, ventilation and cooling. Each system comprises sophisticated machines that are energy intensive. Types of machinery include pumps, compressors, chillers and fans.

Deep level mine equipment

Two important underground safety aspects are air temperature and air quality. The virgin rock temperature (VRT) and exhaust fumes from machinery cause the air to be hot and polluted [8], [11], [12]. Bulk air coolers (BACs) are large structures that use pumps and fans to provide ventilation. Ambient air flows through a cold-water vapour before being sent underground (Figure 1.3) [13]. BACs provide the mining environment with dehumidified air at a temperature of 7°C [13]. Ventilation fans therefore maintain a safe underground temperature while ensuring a safe atmospheric vapour composition [14].

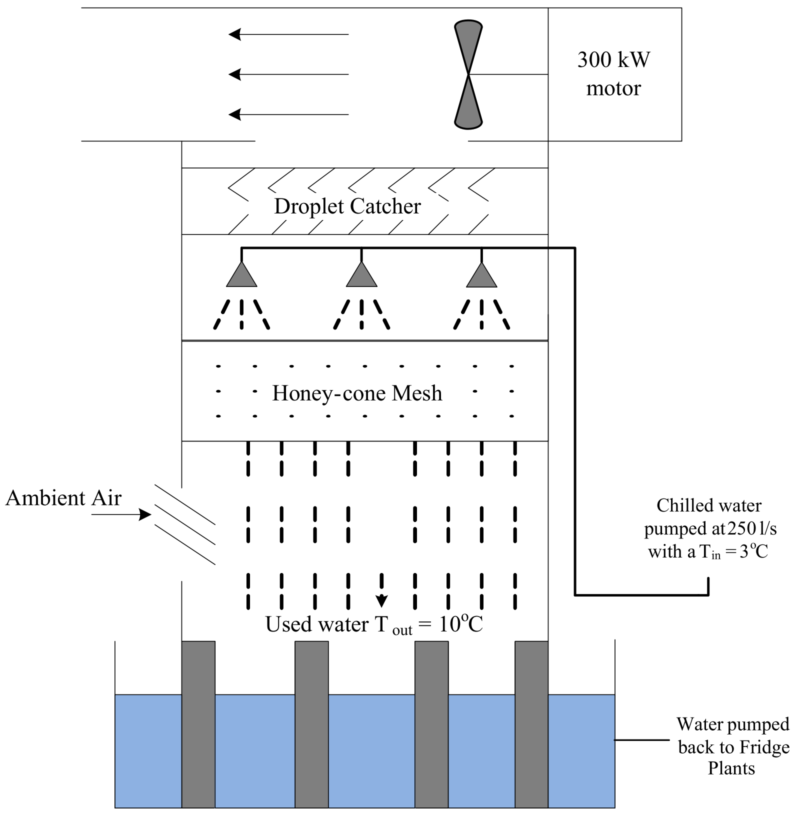


Figure 1.3: *Cross section of a typical BAC* [14]

Depending on environmental and operational factors, mines may install ventilation and cooling plants on the surface and underground [11]. Figure 1.4 shows an underground cooling plant. Industrial chillers provide the cold water that is used by underground operations and ventilation equipment. These chillers typically have a power rating of 1 MW to 5 MW and supply cold water at a temperature of 3°C [15]. Cold water is used to cool down the virgin rock and drilling equipment. It is then gathered in underground hot dams before being pumped back to the refrigeration plants.

Figure 1.4: *Underground refrigeration plant (photo taken on site)*

The water reticulation system uses large pumps to dewater the underground mining levels [16]. Used mine service water as well as fissure water (naturally occurring groundwater), need to be pumped back to the surface to avoid flooding [7]. A common pumping strategy uses sets of pumps and dams located on selected levels [17]. The hot water (typically around 30°C) can thus be pumped on a per-level basis until it reaches the surface. The flow rates of these dewatering pumps range from 100 ℓ/s to more than 250 ℓ/s. Such high flow rates are necessary to pump volumes of 30 Mℓ per day [18]. A mine dewatering pump is shown in Figure 1.5.

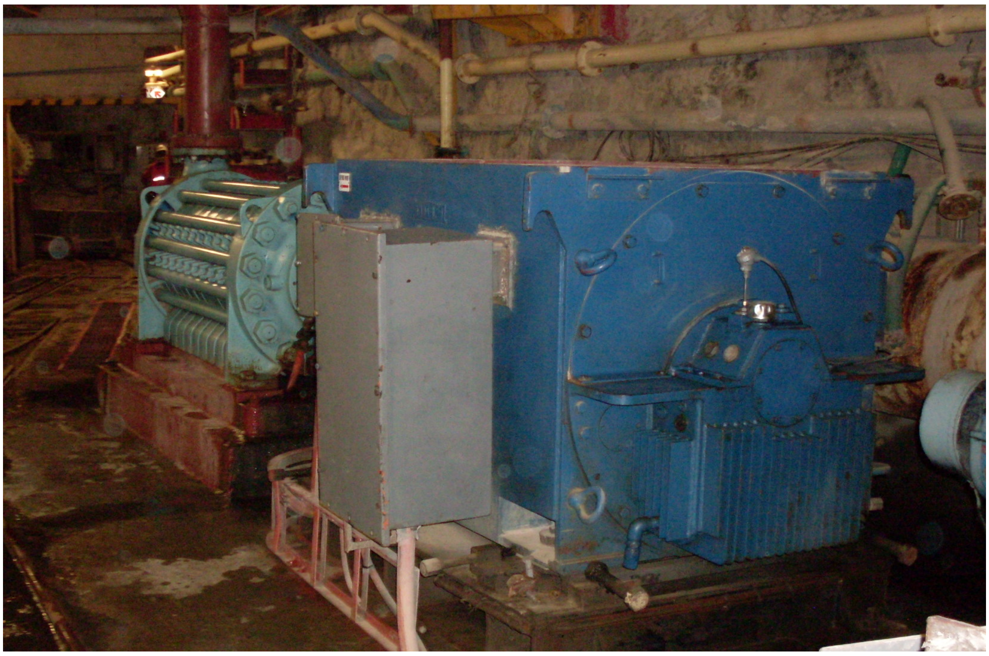


Figure 1.5: *Mine dewatering pump (photo taken on site)*

Compressors account for a significant portion (around 17%) of a mine's total electricity usage [19], [1]. Mines make use of compressor houses that may contain several compressors. These compressors supply air to a compressed air network, consisting of piping installed over great distances. A typical mine compressor is shown in Figure 1.6.

Figure 1.6: *Mine compressor (photo taken on site)*

Compressed air consumers include pneumatic drills, mechanical ore loaders and refuge bays [20]. Air-flow rates of 120 000 m^3/h, at pressures exceeding 350 kPa, are possible [21], [20]. A piping network, with various air valves installed, is used to provide compressed air to the different underground levels.

It is vital that air leaks within the piping network are eliminated as far as possible. Air leakage has a negative impact on energy usage, carbon emissions and equipment longevity. Leaks can consume 20–30% of a compressor's output and is therefore a significant source of wasted energy, as shown in Table 1.1 [22], [23].

Table 1.1: *Power and flow wastage due to air leaks* [23]

Hole diameter	Air leakage at 7 barg	Power required to compress air being wasted
mm	**l/s**	**kW**
0.4 (pin head)	0.2	0.1
1.6 (match head)	3.1	1
3	11	3.5

Schedules of operation

Instrumentation devices fitted to operating equipment measure important process parameters. Most measurements taken on site are linked to a data tag and made available on the site's Supervisory Control and Data Acquisition (SCADA) system [15]. These SCADA tags are used to monitor and control the installed equipment. Control instructions that are submitted on the SCADA platform are transmitted to the Programmable Logic Controller (PLC), which executes the specified command [24]. Automatic or manual control can be used, depending on the infrastructure.

Control-room operators monitor real-time measurements shown on the SCADA system to determine when manual control intervention is needed. A control philosophy contains predetermined control ranges for selected process parameters. It also specifies the type of action that corresponds to each control specification. Process parameters such as pressure, flow or temperature can, for instance, be used to determine when to start or stop a pump.

Automatic control is made possible by industrial control systems that can connect to and communicate with the on-site SCADA system. The control system can automatically write values to control tags (e.g. start or stop tags) if the relevant permission has been granted. These control commands are governed by the control philosophy specification. Figure 1.7 shows an example of such a control system.

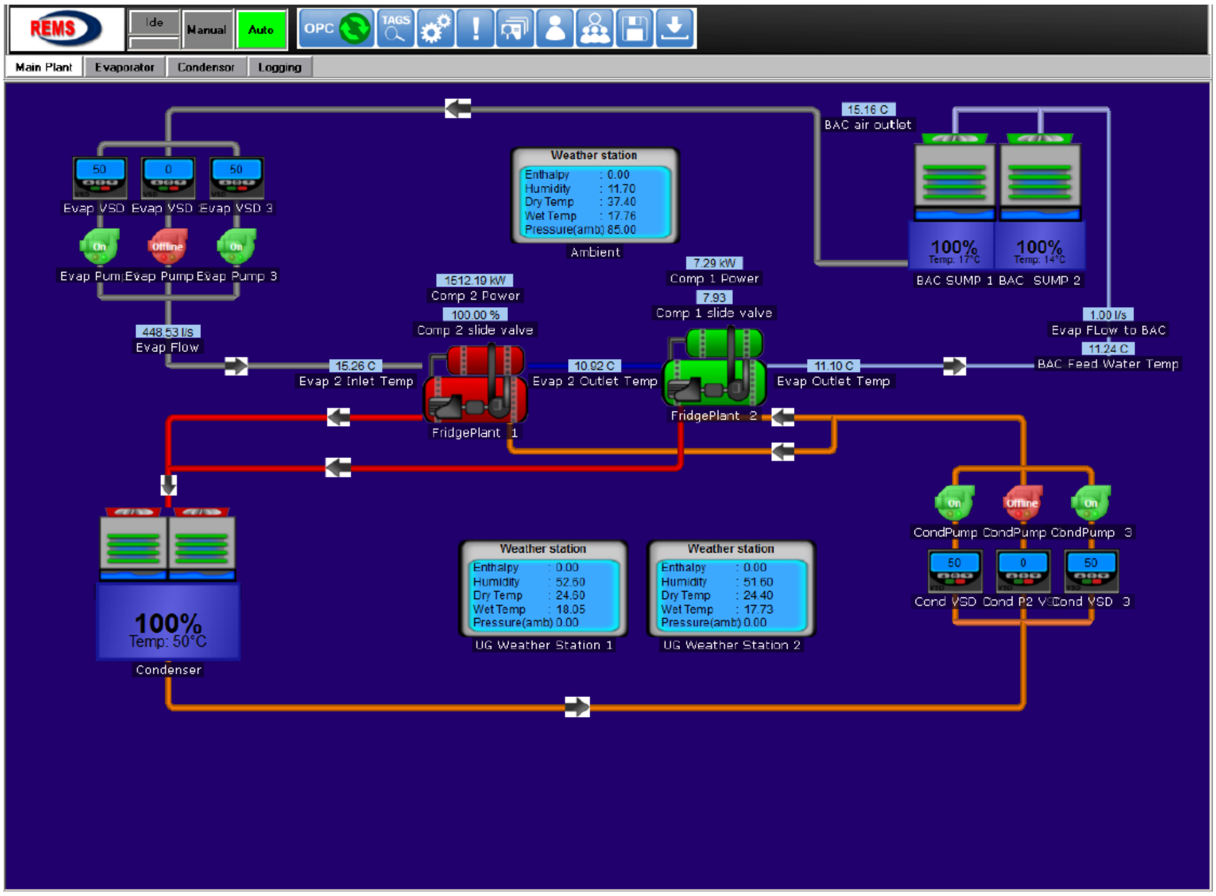


Figure 1.7: *Industrial energy management control system*

It has become customary for mining energy managers to incorporate the cost of their energy usage into the control philosophies [17], [3], [25]. Eskom determines a mine's electricity cost according to time-of-use (TOU) tariff structure [2]. The active energy charge (c/kWh) depends on the time of day, transmission zone, voltage scale and whether it is high demand- or low demand season [2]. During the high demand season (Jun–Aug) the active energy charge for peak period usage is six times the active energy charge for off-peak period usage [26].

Due to the high electricity tariffs, mines regularly engage with energy service companies (ESCOs) to implement energy management strategies [17]. ESCOs use different types of software systems to effectively manage the energy usage. These energy management strategies either reduce the overall energy demand (energy efficiency or load clipping), or allocate energy usage to a less expensive tariff period (load shifting) [27], [28]. Not only does Eskom benefit from the demand reduction, especially during the peak demand periods, but the client benefits from a financial saving.

Operational condition and maintenance

Although the energy usage of mining equipment is monitored and analysed daily, the condition of machines is not adequately assessed [29], [30]. Lack of regular maintenance causes machines to malfunction, become inefficient and finally break down [31]. Figure 1.8 shows an example of damage caused by cavitation.

Figure 1.8: *Pump impeller damage due to cavitation* [32]

Cavitation is only one example of the many possible negative effects of maintenance negligence [33]. Lack of required maintenance results in either an increase in the energy demand (and therefore in the electricity cost), or major repairs, which effectively nullifies the financial savings achieved by energy management projects [34], [35]. Efficient schedules of operation that minimise peak time usage may also no longer be viable due to the maintenance interruption.

Reactive maintenance (repair it when it breaks) takes longer and is usually more expensive than planned maintenance [36], [37]. Several factors need to be considered to determine the true downtime cost of mining equipment. Equipment downtime may have a significant impact on the production output and can also negatively affect the ESCO's energy-saving targets [7]. Due to budget constraints, mines depend on the financial benefit of these energy savings [7]. It can therefore be mutually beneficial to revise the traditional energy management approach by incorporating condition monitoring.

Energy efficiency calculations are readily available, while operational condition considerations are neglected. Operational condition refers to the availability, reliability and the process characteristics of machinery and systems. It is common for maintenance strategies to be time-based (service intervals), due to the challenges involved with incorporating operational conditions into the strategy [37]. The time-based approach is classified as preventative maintenance. Although it improves on reactive maintenance, it is not as effective as proactive maintenance.

Data collection

Mining operations depend on various measurements from the machines in operation. These measurements include machine data (e.g. status, running hours and availability), as well as process data (e.g. pressure, temperature and flow). ESCOs implement energy management projects by using the available site data. A SCADA system localises the entire site's data. ESCOs may procure and install additional instrumentation hardware to make supplementary measurements available on the SCADA system.

An efficient way of data collection is by using software systems to create log files for the required data [24]. These log files can then be sent via email to the respective locations for analysis. ESCOs use this method to obtain and analyse energy data. Energy reports typically contain the energy usage of various subsystems, as well as the total energy usage [29]. The project performance can then be compared to a predetermined budget [2]. Although data validation needs to be done on a continuous basis, the process is relatively simple and can be automated.

In order to assess the operational condition of systems and machines, a large number of parameters need to be considered. This equates to a vast amount of data that needs to be compiled, transferred (email) and translated into information [38]. Consider a pump monitoring process that involves 25 different types of tag measurements per pump. If these tag values are logged every 2 minutes, a total of 720 data points are generated for each individual tag per day. For a mining site with five dewatering levels, consisting of five pumps each, the data points amount to 450 000 per day, or 13.5 million per month.

Information systems

The substantial amount of data makes it clear why an automatic system is necessary to holistically evaluate an entire mining operation [37], [39]. The data cannot merely be measured, compiled and presented to the relevant persons. Key performance indicators (KPIs) need to be determined, benchmark values need to be calculated and the duration of system deficiencies must be indicated. An information system can therefore make it possible to determine the current state of operations and give attention where needed.

A system assessment must, however, be done on a continuous basis to successfully identify problem areas and prevent imminent failures. As mentioned previously, cavitation can cause serious damage to pumping equipment. Cavitation occurs when bubbles implode on the inside of pump vanes due to a decrease in pressure [40], [41]. It is possible to detect component or system defects (such as cavitation) by analysing several parameters (such as flow and vibration) [40].

System inefficiencies can also be detected and addressed. For example, a daily examination of the compressed air distribution can indicate if air leaks exist [20]. Performing a mass flow balance of the air delivery measurements will aid in establishing the amount of air that is being misspent. The information system subsequently enables supervisors to follow up on maintenance requests and verify whether repairs were successful.

Exception reporting

Vital information often goes unnoticed due to feedback reports that contain excessive and unnecessary information [42]. Energy and maintenance managers stating that reports are too detailed, and therefore not looked at, is a common occurrence. Significant indicators must therefore be identified and illustrated in such a way that the information is concise and easy to understand. The focus must be placed on issues that deserve attention. Detailed information regarding these issues can then be provided upon investigation.

The purpose of an exception report is to provide a summary of incidents that can be classified as abnormal. Boundary-level values are used to determine a scope which defines a normal range of operation [43]. Abnormal operation can therefore be identified and listed as an operational exception incident. It is, however, important to monitor the correct parameters to successfully recognise abnormalities that may develop into a serious situation.

Early detection of defective equipment can drastically reduce the repair cost and downtime, as well as extend the operational lifetime of machinery [43], [44]. However, early detection is very difficult if an individual needs to physically inspect an entire mine's installed equipment. Manual inspections are therefore typically done on a monthly basis. The aim of exception reporting is therefore to alert the relevant personnel of operational deficiencies or risks.

1.3 Overview of existing solutions

A literature review was performed to establish the state of the art. Relevant solutions, consisting of maintenance strategies and systems, were identified and categorised (Table 1.2). The legend provides more detail regarding the application and methodology of selected table entries. The categories that make up the focus area of the proposed research are listed in the first four columns. A solution is therefore needed that fulfils these requirements.

Many of these studies have developed a methodology without implementing it in a real-world setting. Instead, experimental setups were used for verification. The majority of condition-based maintenance (CBM) implementations are on manufacturing- or processing plants, while some of the solutions were developed for pump stations. Most of the automated systems require new instrumentation to be purchased and installed.

Considering the focus area of deep level mine equipment, it is clear that the available solutions are inadequate. Thus, a solution that will focus on underground mining equipment is proposed. Available data and infrastructure will be used to assess the operational condition of equipment. An automated system will be developed to facilitate the required functionality. Multiple types of mining system evaluations will be integrated to provide a holistic view of the operational risks.

Table 1.2: *Summary of existing solutions*

	Focus area										
	A	B	C	D	E	F	G	H	I	J	K
	Underground mine equipment	Available infrastructure	Automated system	Multiple mining system analysis	Requires instrumentation	Other type of mining application	Plant/Pump station	Single system analysis	Methodology	Experimental verification	Other industry/ application
Grall et al. [45]									I1	x	
Vagenas et al. [46]						F1		x			
Brax and Jonsson [47]							x				K1
Paya et al. [48]									I2	x	
Wu and Law [49]									I3	x	
Mehala [9]									I4	x	
Mei and Ding [50]									I5		K2
Berge et al. [42]		x	x				x	x	I6		
Chindondondo et al. [51]			x		x			x			K3
Niu et al. [52]			x				x			x	
Brkovic et al. [53]							x		I7	x	
Ahmed et al. [54]									I8	x	
Yam et al. [37]							x		I9		
Kleinmann et al. [55]								x	I10	x	
Jayaswal et al. [56]									I11	x	
Alfayez et al. [57]								x	I12	x	
Kunze [58]			x								K4
Ebersbach and Peng [59]			x								K5
Yang et al. [60]		x						x			K6
SKF @ptitude Asset Management System [61]			x		x		x				
NI InsightCM [62]			x		x	F2					
CI Spider 80X [63]			x		x						K7
Proposed solution	x	x	x	x							

Legend	
F1	Load-haul-dump vehicles
F2	Excavator monitoring
I1	Mathematical models
I2	Artificial neural network (ANN)
I3	Fuzzy robust wavelet support vector classifier
I4	Motor current signature analysis
I5	Dynamic interactions
I6	Technical condition index
I7	Wavelet transform
I8	Compressed sensing, Deep neural network (DNN)
I9	Recurrent neural network
I10	Fuzzy logic
I11	Fast Fourier Transform (FFT), Band pass analysis
I12	Acoustic emission
K1	Equipment manufacturing
K2	Rail vehicle suspensions
K3	Sugar production
K4	Power systems
K5	Processing plant
K6	Wind turbines
K7	Automotive and aerospace

1.4 The need for the study

Deep level mines need innovative solutions in order to remain profitable and competitive. With increased operational costs and reduced commodity prices, these mines are under severe economic pressure:

"*Poor metals price performance had been exacerbated by significant cost pressures propelled in the first instance by rapid power price increases and productivity challenges which arose from the need for continuing above-inflation increases in labour costs while, as mines age, the ore mined is of lower grade, deeper and further from the shafts.*"

– Valli Moosa, chairman of Anglo American Platinum in 2014 [64]

Considering the fact that deep mines need to lower their operational costs and limit any avoidable costs, it is vital that their maintenance strategies are optimised. Costs can be reduced by avoiding unnecessary maintenance and by scheduling maintenance interventions more efficiently [65], [66], [67]. One third of maintenance costs are incurred unnecessarily due to bad planning, overtime cost and misused preventative maintenance [68], [69].

Reactive, or run-to-failure, maintenance performs repairs after the equipment has failed [70] and is commonly used in industry [71], [37]. The maintenance costs related to this type of policy are higher than that of preventative maintenance due to [36], [37]:

- The high cost of restoring equipment to an operable condition under crisis situations;
- The secondary damage and safety hazards inflicted by the failure; and
- The penalty associated with lost production.

International studies have shown that the cost of an unexpected one-day stoppage in industry can range from 100 000 to 200 000 euros [72]. Significant downtime costs due to stoppages can also be observed on deep level mines. South African mines must adhere to the regulations of the Mine Health and Safety Act (MHSA) and can be forced to discontinue operations if found to be non-compliant. In one such an example, where an entire mine was shut down, the financial impact was calculated to be R 9.5 million per day [73]. This example demonstrates the magnitude of the financial impact resulting from extended production delays on a mine. Effective maintenance is therefore necessary to avoid unplanned stoppages due to equipment or system failures.

Fraser *et al.* conducted a critical review regarding real-world applications of various maintenance models [30]. More than 2 000 research papers were included in their survey. The authors stressed the fact that a gap exists between academic research that only contains theoretical results, and studies with empirical evidence from practical implementations. Their findings included the fact that, for every 33 articles that focused on maintenance strategies, only one contained empirical work. Three additional research papers that support these findings stated the following:

– *Although literature on CBM is available, the application of CBM in practice is lagging behind* [74].

– *Many mathematical models are very complex and difficult to implement in practice* [50].

– *Maintenance literature is strongly biased towards new computational developments, which are of questionable practical value* [75].

Three maintenance management models were identified by Fraser *et al.* [30] to be dominant in literature:

- Total productive maintenance (TPM);
- Condition-based maintenance (CBM); and
- Reliability-centred maintenance (RCM).

Case studies where these maintenance models were implemented were divided into research sectors and industries. Table 1.3 lists the various industries together with the number of implementations for each.

Table 1.3: *Maintenance models – Sector implementations* (Compiled from [30])

Research sector	Research industry	Count	Research sector	Research industry	Count
Manufacturing	General	5	Energy	Power plant	6
	Automotive	3		Hydropower	2
	Semiconductor	4		Distribution	1
	Machinery	1		Oil refinery	1
	Steel plant	4		Wind farm	1
	Installation/systems	1		Gas production	1
	Airbags	1	Transport	Railway	1
	Soft drinks	1		Aviation	1
	Paper	2	Operations	Foundry	1
	Ceramics	2	Health care	Hospitals	1
	Electronics	1	Food processing	Plant and equipment	1
	Part supplier	3	General	General	12
	Tyres	1	Construction	Housing	2
	Timber mill	1	Service	Libraries	1
	Various	15			

It is evident that most of the implementations are performed within the manufacturing sector. The list does not contain any implementations within the mining industry. Applicable case studies were also not found in more recent published literature.

A need therefore exists to investigate the feasibility of CBM on deep level mines. An effective maintenance strategy may consist of using both CBM and time-based maintenance. Due to the size of a mining operation, an automated information system is needed to continuously collect and analyse the various types of data. This would facilitate the development of a CBM strategy by enabling maintenance professionals to examine the operational risks that were identified, and schedule maintenance investigations accordingly.

1.5 Problem statement and objectives

The condition of installed equipment plays a major role in a mine's production output. The previous sections have shown that a deep level mine faces many challenges when it comes to the maintenance of machinery and the monitoring of equipment's operational condition. A problem statement was therefore formulated to summarise the need for a solution:

Equipment reliability has a significant impact on mine safety and productivity. It is, however, labour-intensive to evaluate the operational condition of deep level mine equipment. Existing maintenance solutions for underground mining are inadequate when considering a condition-based approach. A system is needed to analyse various parameters of mining machinery on a continuous basis. For such an analysis to be practical and efficient, it must be done automatically.

In order for the solution to address the problem elements, the objectives and scope of the system have been identified as follows:

- To automatically identify operational risks on mining equipment;
- To automatically generate risk notifications and evaluations;
- To eliminate the labour-intensive task of collecting, structuring and examining machine and process data;
- To promote transparency regarding the operational condition of equipment throughout the corporate structure;
- To integrate CBM approaches with existing maintenance strategies; and
- To promote the safety of underground mining operations.

1.6 Novel contributions

This section lists the contributions made by the research presented in this study. The originality of the contributions is proven by discussing existing solutions and the relevant shortcomings thereof.

A strategy to make use of available data and infrastructure to facilitate CBM on deep mines

The need – Mines need to reduce their operational costs to remain profitable. Solutions requiring high capital expenditure cannot be considered due to cash flow constraints. CBM can reduce operational and maintenance costs by avoiding unplanned maintenance and equipment downtime.

Existing solutions – Industrial manufacturers provide condition monitoring solutions that typically require additional instrumentation to be purchased and installed.

Shortfalls – Deep mines have a vast and complex network of systems and installed equipment. It is not feasible to procure and retrofit multiple sensors per system, due to the required capital expenditure.

Proposed solution – Available infrastructure will be used to obtain the required machine- and process data. Data loggers that interface with the mine's SCADA system will be configured to log selected parameters. An existing data translation system will be used for the preparation and storage of the incoming data. An existing online platform, previously developed to display energy-related data, will be adapted to display asset health information and enable users to monitor equipment remotely via the internet.

An innovative methodology to evaluate the operational condition of deep level mine equipment

The need – Deep mine operations consist of multiple systems, which include water reticulation, compressed air, ventilation and cooling. These systems make use of equipment located on surface, as well as on various underground mining levels. Several types of input parameters need to be considered when evaluating the condition of mining equipment.

Existing solutions – Highly specialised and in-depth analyses have been developed to evaluate equipment condition. These methods typically require specialist measurement equipment and expert knowledge.

Shortfalls – It is not feasible to perform regular in-depth analyses on all the required mining systems. This is mainly due to the high number of parameters that need to be analysed, the limited access to equipment and the limited number of specialist resources available.

Proposed solution – A methodology will be developed to evaluate multiple types of input parameters continuously. These parameter evaluations will be combined into a single graphical result to ease the identification of operational risks. The methodology will be designed to be included in an automated process. This would enable maintenance supervisors to focus on the results from the assessment, rather than the assessment itself. It would furthermore require a reduced number of personnel to determine where additional investigations are needed.

A new integrated information system for deep mines

The need – Deep mines operate at depths of 3 km below surface. Underground entry is restricted during blasting shifts and is otherwise time-consuming. This makes equipment monitoring a challenging task.

Existing solutions – Mine information systems and SCADA platforms are mainly used to view and store data on site. Data analyses are typically performed on an *ad-hoc* basis.

Shortfalls – Too much data and too little information make it very labour-intensive to determine where attention is needed. A manual process has a linear relationship between the number of input parameters and the time it takes to analyse them. Additional time and resources are therefore needed for each additional system that needs to be monitored. Data stored on site is also not readily accessible to external stakeholders.

Proposed solution – An information system will be developed to automatically collect data, perform a data analysis and generate risk notifications. The scalability of the automated system makes it possible to keep adding more parameters and systems without having an adverse effect on the processing time. The raw data and risk notifications will also be made available online. Personnel can therefore access the required information remotely.

A practical evaluation of a CBM strategy on deep level mines

The need – A need exists to investigate the use of CBM on deep level mines. Literature has shown that many maintenance strategies are only validated with experimental results. Due to the dynamic nature of a mining environment, it is necessary that theoretical methods be evaluated in practice.

Existing solutions – CBM techniques are predominantly developed for the manufacturing sector. Many theoretical studies have shown potential CBM techniques.

Shortfalls – Maintenance on a plant differs greatly from an underground mine. A plant is a controlled environment with easy access to equipment. The limited access to equipment on a mine means that visual inspections are only performed when considered critical. Theoretical solutions cannot consider all the external factors on a mine that impact maintenance strategies.

Proposed solution – The developed health assessment methodology and information system will be validated with actual site implementations. Multiple mining systems on multiple mining sites will be evaluated. This will provide empirical results regarding the feasibility of CBM on deep mines.

1.7 Thesis outline

This section gives an overview of the thesis structure. A narrative that illustrates the development process from problem formulation to solution implementation is provided. Figure 1.9 below demonstrates how the thesis elements are organised.

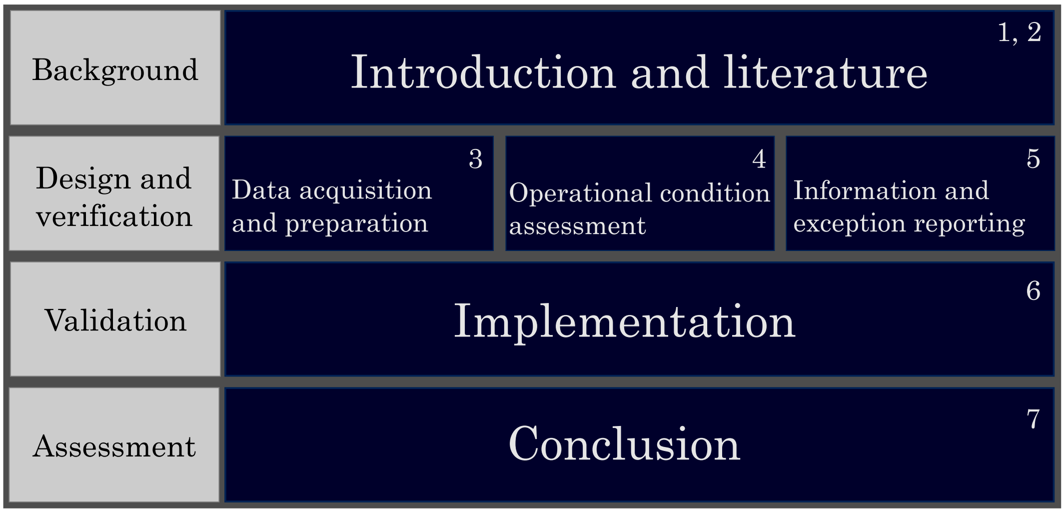


Figure 1.9: *Thesis outline*

Chapter 1 describes the context of the problem and provides some relevant background information. The first chapter also contains an overview of existing solutions, to establish the state of the art. *Chapter 2* reviews and discusses applicable literature pertaining to the fields of condition monitoring and maintenance. *Chapters 1* and *2* therefore aim to answer *why* the study was conducted and to explain *what* the objectives of the proposed solution are.

Chapters 3, 4 and *5* each comprises a design specification and a verification section regarding the relevant subsystems. These chapters therefore show *how* the solution was developed.

Chapter 6 provides the practical implementation details. The measured results serve as *validation* for the system that was developed.

Chapter 7 discusses the work that was done. An *assessment* of the results examines key points and identifies future opportunities.

The main elements of the information system are discussed in the three design chapters. Figure 1.10 shows the elements that each of these chapters consist of. *Chapter 3* focuses on the acquisition and translation of data. The data analysis and risk assessment methodology are documented in *Chapter 4*. *Chapter 5* covers the control system alarm procedure, as well as the development of the web interface and the automated reports.

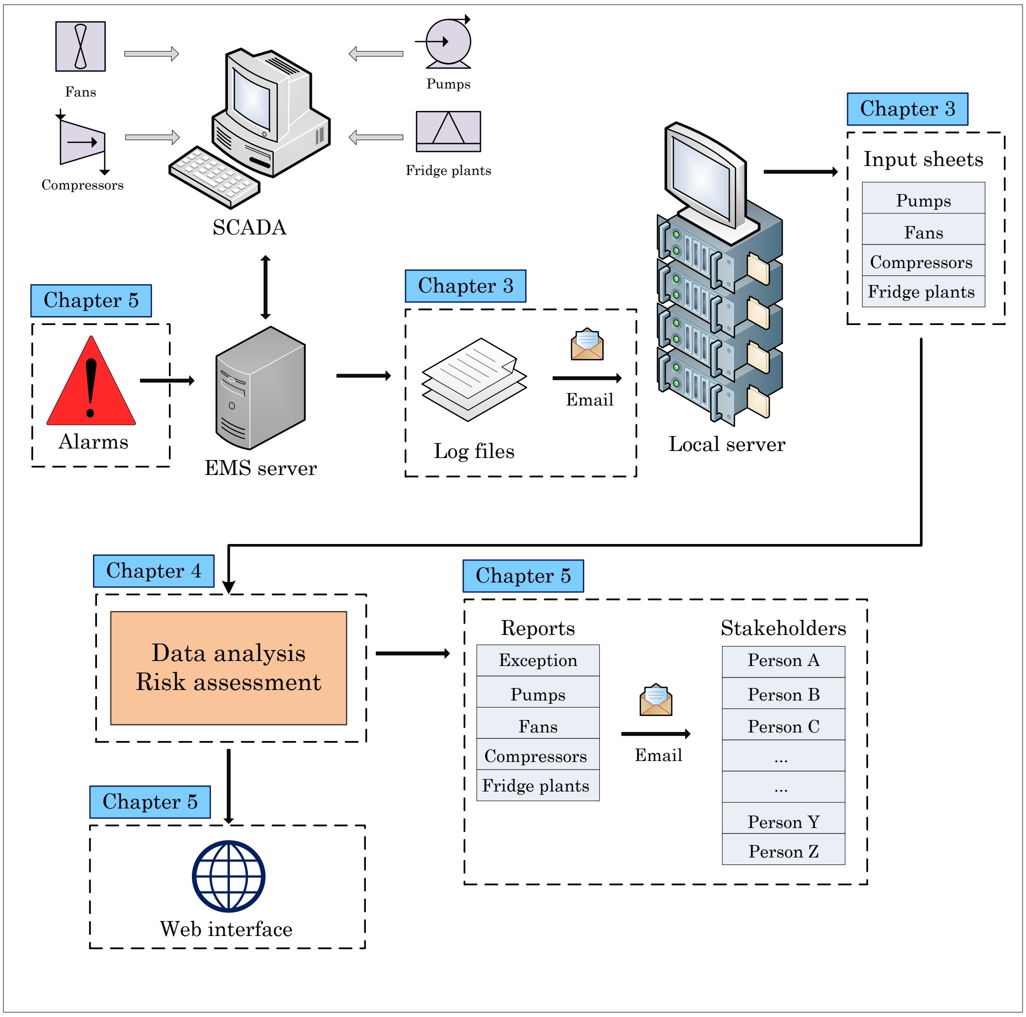


Figure 1.10: *Overview of the data analysis process*

CHAPTER 2

Literature review

2.1 Preamble

One of the world's leading gold producers, Newmont Mining Corporation, estimated that the replacement cost associated with a component that has failed is five to seven times the pre-failure replacement cost [34]. In addition to replacement costs, premature component failures are some of the largest contributors to lost production and additional, mostly unplanned for, maintenance costs [34].

Different types of maintenance systems and strategies have been developed to increase equipment availability and reduce maintenance-related costs. One such an approach is remote CBM, where equipment monitoring is performed from a location that is not in the immediate vicinity of the site or operation [76]. *E-monitoring machine health systems* or *Internet CBM* are terms that are used when making CBM information available online via web pages on the internet [76].

E-technologies make it possible to assess larger data volumes over a large geographical area [77], [78]. Users can subsequently make more informed decisions and collaborate with different teams [77]. E-maintenance, in terms of a strategy, refers to the use of digital technologies to obtain real-time equipment data, which makes it possible to manage tasks electronically [77]. Muller *et al.* [77] states that: "*An e-maintenance platform introduces an unprecedented level of transparency and efficiency.*"

Another type of e-technology is a decision support system (DSS). A DSS is a digital information system containing domain-specific knowledge [37]. It is intended to enhance decision-making by facilitating information management and increase awareness of deficiencies [37].

Deep mine operations comprise complex systems and processes and are generally located at remote locations. These mining operations rely on equipment availability to ensure uninterrupted production and maintain a safe working environment. Several maintenance managers at a large South African mining group confirmed that their maintenance strategy consisted of time-based maintenance (inspections are performed periodically) and reactive maintenance (repair it when it breaks). Effective deep mine maintenance will, however, require a combination of an information system, e-maintenance, remote CBM and DSS functionality.

2.2 Theoretical background

Different types of quantitative and qualitative methods are used to evaluate asset health and reliability. Depending on the available information, some methods might not be viable for certain types of applications. Regarding mining maintenance, there exists a gap between what is theoretically possible and what is practically feasible. It is, however, important to investigate and understand the available techniques in order to determine which methods can be considered for implementation.

Equipment and system reliability

Reliability and availability of equipment and systems are vital in an underground mining environment. Failure to manage the level of risk exposure may necessitate the mine to halt production, or compromise the safety of the underground workers. Several evaluation methods are used to quantify the reliability of a system or subsystem. A few that are typically considered are discussed below.

Mean Time Between Failures (MTBF)

Definition: The average, or expected, time between consecutive component failures [79], [80].

Equation(s):

$$MTBF = \frac{Total\ operating\ time}{Total\ number\ of\ repairs} \tag{2.1}$$

$$MTBF = \frac{\sum_{i=1}^{N_F} x_i}{N_F} \tag{2.2}$$

where N_F is the total number of failures and x_i is the time elapsed from the $(i-1)^{th}$ failure to the i^{th} failure [81].

Usage: MTBF is typically expressed in units of hours [79]. Since numerous *failure* definitions exist, it is important to clearly define what failure means in the current context. MTBF is worthless if failure is ill defined. It is also important to understand how to interpret the MTBF figure. Torell and Avelar [80] illustrates how the MTBF of humans can be calculated to be 800 years, while their life expectancy is closer to 80 years. This is because MTBF is based on the *useful life* period, where the failure rate is assumed to be constant.

Mean Time to Repair (MTTR)

Definition: The expected time to restore or recover a system from a failure [80].

Equation(s):

$$MTTR = \frac{Total\ repair\ time}{Total\ number\ of\ repairs} \tag{2.3}$$

Usage: MTTR is also typically expressed in units of hours. The time to repair can include the time it takes for a technician to arrive on site, the time it takes to perform a diagnosis and the repair time. The MTTR influences the equipment availability (Equation 2.5), but not the reliability (Equation 2.6).

Availability

Definition: The percentage of time that a system is operating satisfactorily [82]. It is the degree to which a system or component is operational and accessible when required for use [80].

Equation(s):

$$Availability = \frac{Total\ uptime}{Total\ uptime\ +\ Total\ downtime} \tag{2.4}$$

$$Availability = \frac{MTBF}{MTBF\ +\ MTTR} \tag{2.5}$$

Usage: It can be viewed as the likelihood that the system or component is in a state to perform its required function under given conditions at a given instant in time. Availability is determined by a system's reliability, as well as its recovery time when a failure does occur.

Reliability

Definition: The ability of a system or component to perform its required functions, without failure, under given conditions for a specified time period [82], [80].

Equation(s):

$$Reliability = \mathrm{e}^{-\left(\frac{Time}{MTBF}\right)} \tag{2.6}$$

Usage: Equation 2.6 provides another way of interpreting MTBF. A higher MTBF figure results in higher reliability.

Equipment and system condition

Multiple methodologies, using multiple analysis techniques, have been developed to classify equipment condition. These analysis techniques have different advantages and requirements. Signal processing methods are commonly used to analyse vibration signals [54], [83]. Statistical analyses, fuzzy logic and neural networks have been used to evaluate other types of input parameters [84], [55], [52], [33]. Selected methodologies are listed below and some will be briefly discussed.

The following techniques have been used for fault diagnosis and condition monitoring:

- Artificial neural network (ANN) [84], [48];
- Deep neural network (DNN) [54], [85];
- Recurrent neural networks (RNN) [86];
- Fuzzy logic [55], [49];
- Composite hypothesis test theory [87];
- Support vector machine (SVM) [83]; and
- Wavelet theory [49], [48].

Neural networks

Artificial neural networks (ANNs) were designed to mimic the biological neuron and have been used in the fields of identification and classification [48]. ANNs consist of a number of artificial processing neurons, or nodes, which are grouped together in various layers to form a network [48]. Figure 2.1 shows a typical ANN consisting of two layers (one hidden layer and the output layer). The number of hidden layers and the nodes within each hidden layer is usually a trial-and-error process [48].

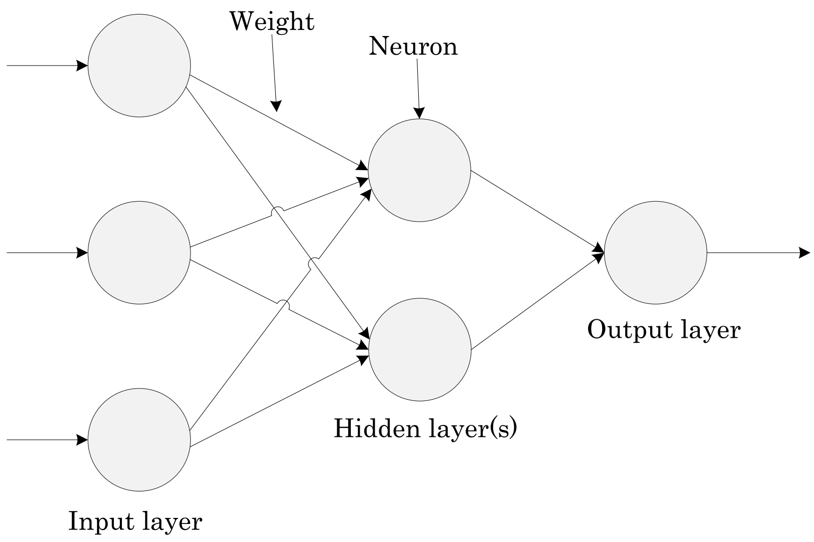


Figure 2.1: *A typical two-layered ANN* [48]

ANNs undergo a supervised training procedure for it to be able to analyse and classify new test data (Figure 2.2). The hidden layer nodes multiply the relevant input value (X_i) with the corresponding weight value (W_i), denoted as the product term. A bias value (θ_i) can be added to the product term to shift the sum relative to the origin. The summation result is passed through an activation function, typically a sigmoid function. The difference between the output value and the desired output is expressed as a mean square error (MSE). Backward-propagation can be used to adjust the weights until the MSE is acceptable.

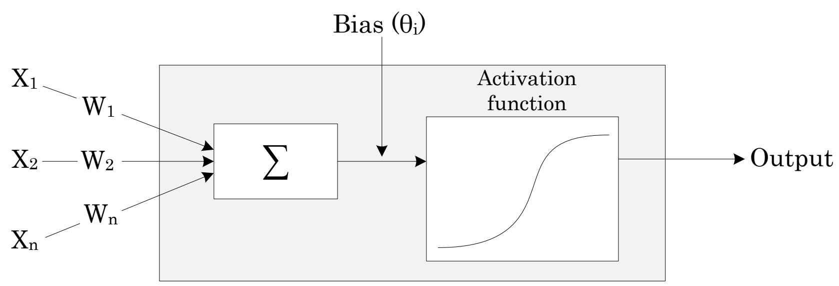


Figure 2.2: *Operation of an artificial neuron in a layer* [48]

A neural network can be used to analyse an input signal such as motor vibration. Neural network software can be used to train the network with training data sets, once the layer topology (number of layers and corresponding nodes) has been established. The training data will therefore need to consist of various vibration signals that were measured on equipment with known defects.

Neural networks consisting of only a few layers are typically referred to as shallow networks [85]. Multi-layered networks are classified as DNNs due to the depth of the layers and nodes. Although Hinton *et al.* [88] developed a deep-learning model comprising three layers, no universal definition is available regarding the required number of layers in a DNN [85]. Figure 2.3 shows an example of a DNN with three hidden layers.

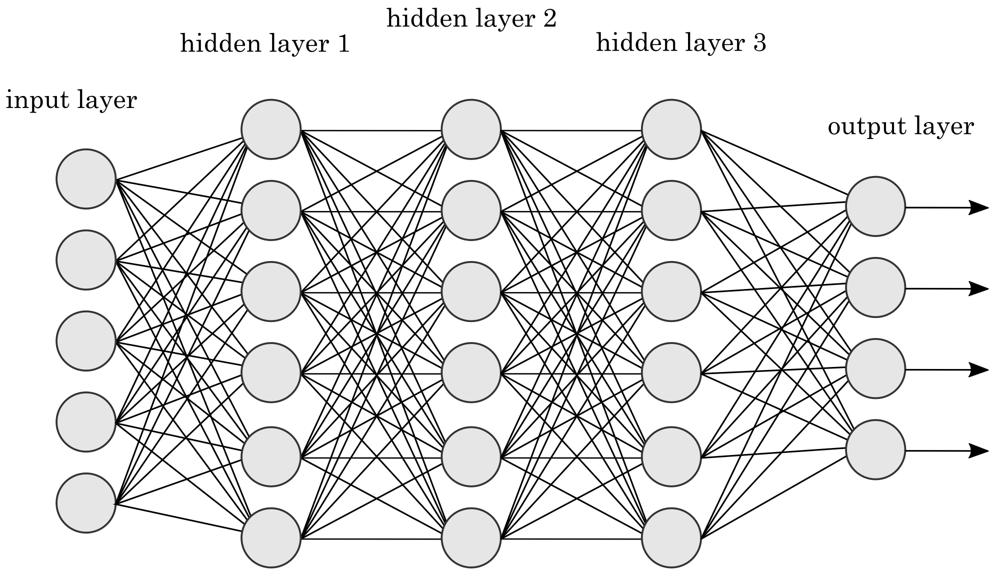


Figure 2.3: *Example of a neural network with three hidden layers*

DNNs can be trained by means of unsupervised learning, which makes deep learning more practically feasible than ANNs [54]. Unsupervised learning is a form of pre-training with the aim of accelerating the supervised learning phase [85]. Auto-encoders and clustering are some of the techniques that have been used in unsupervised learning processes [54], [89].

Ahmed *et al.* [54] used a DNN to identify and classify bearing faults. Vibration data in the form of highly-compressed measurements were analysed. A test rig was used to record the vibration for different types of fault conditions at different speeds. Their method of compressive sensing requires fewer measurements and reduces the computational complexity.

Fuzzy logic

The concept of fuzzy logic was first introduced by Zadeh [90] in 1965. Zadeh stated that real-world data is defined by non-distinct boundaries. The aim was therefore to replace binary values $\{0, 1\}$ with continuous interval values $[0, 1]$. Fuzzy theory enables the representation of linguistic constructs such as *many*, *low*, *medium* and *few* [91]. Fuzzy logic methods make it possible to work with these types of *fuzzy* sets that are approximate, rather than exact.

Fuzzy sets differ from the customarily used crisp sets. Crisp sets only allow full or no membership, while fuzzy sets allow partial membership [92]. Zadeh proposed a grade of membership such that the transition from membership to non-membership is gradual instead of abrupt. An item's grade of membership is represented by a real number between zero and one, commonly denoted by the Greek letter μ [93]. Figure 2.4 illustrates this difference between the membership functions of a crisp set (A) and a fuzzy set (B).

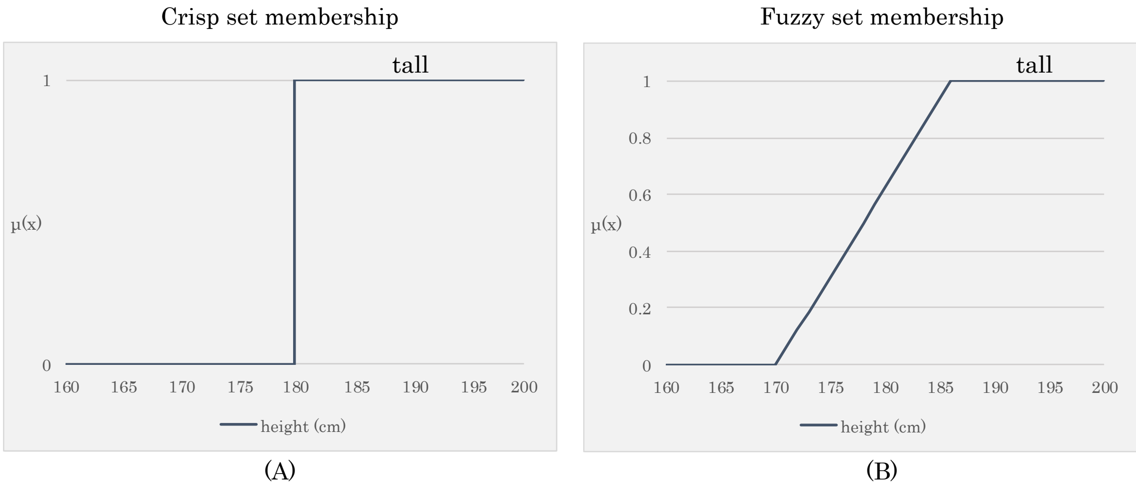


Figure 2.4: *Example of a crisp- and fuzzy membership function*

Several types of membership functions exist to define multiple sets. The choice of membership function should be based on the given problem to optimise the results [91]. Triangular and trapezoidal membership functions are widely used to represent the relevant definitions [91]. The function definition for a trapezoidal membership function is given below:

$$f(x;a,b,c,d) = \begin{cases} 0 & \text{for } x < a \\ \dfrac{x-a}{b-a} & \text{for } a \leq x < b \\ 1 & \text{for } b \leq x < c \\ \dfrac{d-x}{d-c} & \text{for } c \leq x < d \\ 0 & \text{for } d \leq x \end{cases}$$

An example of the trapezoidal function being used to represent multiple sets of height classifications can be seen in Figure 2.5. From the figure it can be observed that a height of 187 cm can be defined as both medium and tall.

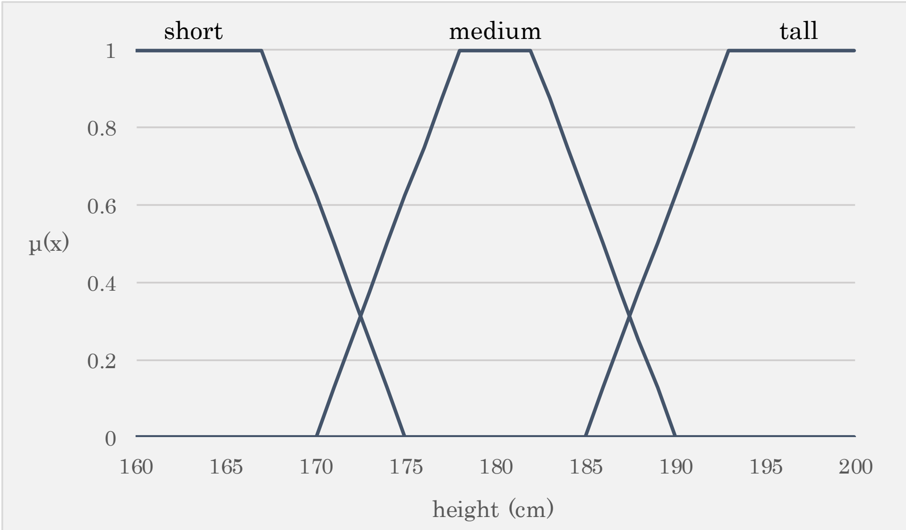


Figure 2.5: *Example of a trapezoidal membership function*

A set of if-then rules are used to specify the relationship between the input and output fuzzy sets [92]. These rules are used by a fuzzy inference system to map the input data vector to a scalar output. The fuzzification process translates the crisp input values to the respective linguistic terms. The grade of membership for an input of 174 cm, using the membership function shown in Figure 2.5, can, for example, be expressed as follows:

$$\mu_{short}(174) = 0.125$$
$$\mu_{medium}(174) = 0.5$$
$$\mu_{tall}(174) = 0$$

Fuzzy logic operators can be used to evaluate partial memberships. Some of these operators are given below:

$$\mu_{A \cup B}(x) = \max[\ \mu_A(x),\ \ \mu_B(x)\ ]$$
$$\mu_{A \cap B}(x) = \min[\ \mu_A(x),\ \ \mu_B(x)\ ]$$
$$\mu_{\overline{A}}(x) = 1 - \mu_A(x)$$

A fuzzy inference system (FIS) is used to perform the analysis. The FIS contains a fuzzifier process module that maps crisp input values into fuzzy memberships, according to the given membership functions and rules. The output of the individual rules is aggregated to obtain a single fuzzy set. The FIS finally uses a defuzzifier to translate the fuzzy set into a crisp number.

One of the most popular defuzzification methods is the use of the centroid (centre of gravity) of the aggregated set [92]. Equation 2.7 provides a formula to calculate the centroid, while Figure 2.6 illustrates the result.

$$C = \frac{\sum \mu(x_i) \cdot x_i}{\sum \mu(x_i)} \tag{2.7}$$

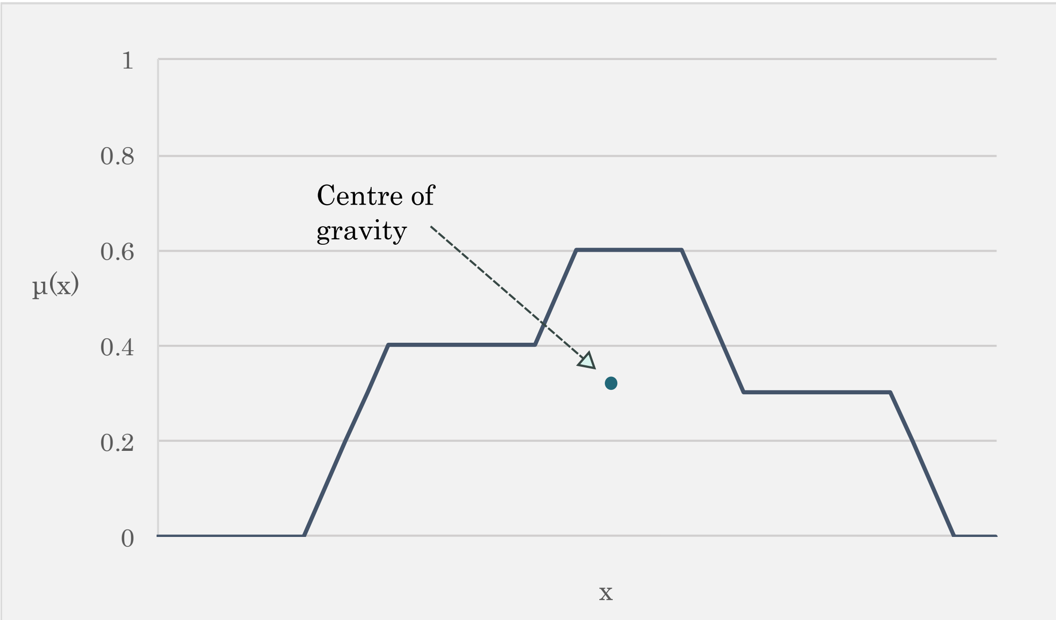


Figure 2.6: *Centroid method illustration*

Kleinmann *et al.* [55] developed a method to assess the health status of a pumping system. The method is based on fuzzy inference combined with a failure modes and effects analysis (FMEA). An experimental pump setup was used to evaluate various degradation indicators. The MATLAB[1] Fuzzy Logic Toolbox was used to perform the rule evaluation and calculate the output. MATLAB is an advanced numerical software suite that is used in many engineering disciplines.

[1]https://www.mathworks.com/products/matlab.html

2.3 Condition-based maintenance

CBM is a maintenance approach where maintenance decisions are made according to a system's current state of degradation [71], [94], [51], [65]. Condition monitoring information is therefore used to determine where maintenance is needed. CBM is used in an attempt to avoid unnecessary maintenance [71], [36]. The CBM process consists of three steps [71], [70]:

- Data acquisition;
- Data processing; and
- Maintenance decision-making.

The main objective of a CBM strategy is to prevent equipment damage and failure. The following section will discuss equipment failure in more detail.

Equipment failure

Three failure types to consider are infant mortality, random failures and time-dependent failures [95], [68]. The well-known bathtub curve is a graphical depiction of the failure rate of some types of equipment [79]. With this type of failure model the failure rate is highest during the early stages (infant mortality) and the wear-out period.

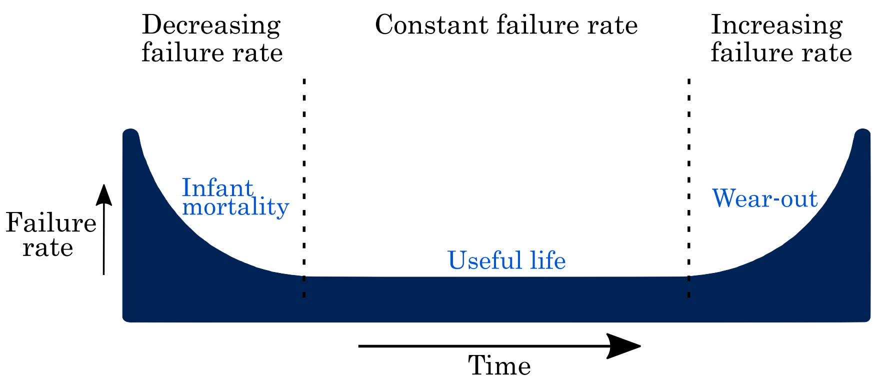


Figure 2.7: *Bathtub curve failure pattern*

Although there exist some cases where industrial equipment follows this failure pattern, the random failure pattern is much more prevalent [79]. A random failure pattern exhibits a constant failure rate over the lifetime of the equipment. It is therefore important to take note of the fact that equipment failure rates do not necessarily increase over time. Infant mortality is, however, a common occurrence [79]. Premature failures may be attributed to deficiencies regarding the design, manufacturing process and assembly [95]. Hence, effective maintenance requires the continuous evaluation of the equipment's operational condition.

Several types of failure classifications are presented in [95]. Some of these classifications include:

- Degree of failure
  - Complete failure
  - Partial failure
- Speed of failure
  - Sudden failure
  - Gradual failure
- Cause of failure
  - Wear-out failure
  - Misuse failure

It is also important to define *system failure* and *component failure* within the relevant context [95]. A pump failure could cause the water reticulation system to fail, if losing the pump renders the pumping capacity of the system to be insufficient. An FMEA enables personnel to determine whether maintenance is urgent, or whether it can be deferred until some future date that is convenient [52].

The literature reviews from [33] and [96] discus several induction motor defects and fault detection methods. Motor defects that commonly occur include:

- Bearing failure;
- Bearing misalignment;
- Rotor broken bars;
- Rotor misalignment;
- Rotor unbalance;
- Bearing loss of lubrication;
- Stator earth faults; and
- Damage to insulation.

While 80% of rotating equipment issues are related to misalignment and unbalance [96], 40% of motor failures can be attributed to bearing-related defects [97]. Figure 2.8 shows the major causes of failure for induction motors.

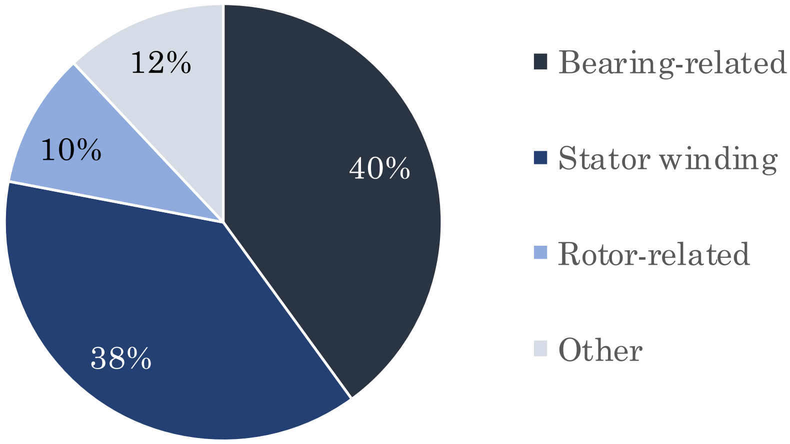


Figure 2.8: *Cause of induction motor failure* [97]

Component defects can cause the machine to malfunction. If these defects are not identified and attended to, it could result in a functional failure [36]. Table 2.1 lists some types of centrifugal pump malfunctions. A common cause for pumps to malfunction is cavitation [40]. Cavitation is an undesirable phenomenon that occurs when micro bubbles form on the impeller due to a rapid change in pressure, and then subsequently implode. Riesz *et al.* [41] noted that, during the final stage of the collapse, the temperature and pressure of the liquid-gas interface can approach 3 000°K and 1×10^6 kPa respectively. Not only does cavitation diminish the mechanical integrity of a pump, it also results in a loss of efficiency [57].

Table 2.1: *Malfunctions of centrifugal pumps with explanations* [98]

Faults	Explanation and consequence
Cavitation	Development of vapour bubbles inside the fluid if static pressure falls below vapour pressure. Bubbles collapse abruptly leading to damage to the blade wheels and generating a crackling sound.
Gas in fluid	A pressure drop leads to the appearance of solved gas in the transported liquid. A separation of gas liquid and lower head may result.
Dry run	Missing liquid leads to lack of cooling and overheating of bearing. Important for starting phase.
Wear	*Erosion*: Mechanical damage to walls because of hard particles or cavitation *Corrosion*: By aggressive fluids *Bearings*: Mechanical damage through fatigue and metal friction, generation of pittings and rents *Plugging of relief boreholes*: Leads to overloading of axial bearings *Plugging of sliding ring seals*: Leads to higher friction and lower efficiency *Increase of split seals*: Decreases efficiency
Deposits	Deposits of organic material or through chemical reactions at the rotor entrance or outlet lead to less efficiency, higher temperatures until total breakdown of pump
Oscillations	Unbalance of the rotor through damage or deposits at the rotor, damage to the bearings

Condition monitoring

It is imperative that equipment is continuously monitored in order to implement a CBM strategy [70]. This is referred to as condition monitoring, where the actual state of an item is observed [70]. The aim is therefore to collect and assess condition data to identify possible risks of failure. Tsang [36] describes these risks as failure symptoms:

It should be noted that an incipient functional failure may show several types of symptoms, each of which may become detectable at different stages of degradation of the unit.

Changes in parameter values, resulting from some form of equipment damage, can therefore be labelled as failure symptoms. A symptom is an observable effect of a fault (component malfunction) [99]. Fault diagnosis refers to the detection and isolation of a fault. Indicating that a fault exists can be defined as fault detection, while determining where the fault is can be defined as fault isolation [99]. Fault prognosis is a forecast of future events, meaning failure predictions are therefore made before they occur [71], [72]. A condition monitoring information system can therefore assist maintenance supervisors with fault diagnostics and prognostics [78].

Condition monitoring techniques or methods typically include motor current, vibration, temperature, torque and noise analyses [100], [96], [44]. A condition monitoring strategy will thus be developed according to the operating environment, the types of equipment and the available input parameters. Several international standards have been developed to provide condition monitoring definitions, classifications and guidelines. Some of these standards are listed in Table 2.2.

Table 2.2: *ISO standards related to condition monitoring*

Standard	Title
ISO 10816–3:2009	Mechanical vibration – Evaluation of machine vibration by measurements on non-rotating parts – Part 3: Industrial machines with nominal power above 15 kW and nominal speeds between 120 r/min and 15 000 r/min when measured in situ [101]
ISO 13381–1:2015	Condition monitoring and diagnostics of machines – Prognostics – Part 1: General guidelines [102], [103]
ISO 17359:2011	Condition monitoring and diagnostics of machines – General guidelines [104]

According to maintenance managers at a large mining group, the ISO standards are used as a guideline when monitoring assets. These ISO standards are only some that are available on the subject of condition monitoring.

ISO 10816 discusses several aspects regarding the evaluation of industrial machine vibration. Vibration magnitude can be evaluated by means of four evaluation zones that permit a qualitative assessment of the vibration [101]:

- *Zone A*: The vibration of newly-commissioned machines would normally fall within this zone.
- *Zone B*: Machines with vibration within this zone are normally considered acceptable for unrestricted long-term operation.
- *Zone C*: Machines with vibration within this zone are normally considered unsatisfactory for long-term continuous operation. The machine may generally be operated for a limited period in this condition until a suitable opportunity arises for remedial action.
- *Zone D*: Vibration values within this zone are normally considered to be of sufficient severity to cause damage to the machine.

Suggested evaluation zone boundaries are also provided in the ISO 10816 standard. The vibration boundaries are given as root mean square (RMS) values. RMS values can be converted to zero-to-peak values by multiplying with $\sqrt{2}$ [101]. Table 2.3 lists the zone boundaries that apply to mining machinery. These machines have power ratings that range from 300 kW to 50 MW and a shaft height of more than 315 mm.

Table 2.3: *Vibration severity zone classification for large machines* [101]

Support class	Zone boundary	RMS displacement (µm)	RMS velocity (mm/s)
Rigid	A/B	29	2.3
	B/C	57	4.5
	C/D	90	7.1

ISO 17359 lists several condition monitoring parameters for various types of machinery. The four major equipment types that will form part of the underground mine evaluation are shown in Table 2.4.

Table 2.4: *Condition monitoring parameters for types of equipment* [104]

Parameter	Machine type			
	Electric motor	Pump	Compressor	Fan
Temperature	•	•	•	•
Pressure		•	•	•
Pressure (head)		•		
Pressure ratio			•	
Air flow			•	•
Fluid flow		•	•	
Current	•			
Voltage	•			
Resistance	•			
Input power	•	•	•	•
Output power	•			
Noise	•	•	•	•
Vibration	•	•	•	•
Acoustic technique	•	•	•	•
Oil pressure	•	•	•	•
Oil consumption	•	•	•	•
Oil (tribology)	•	•	•	•
Torque	•		•	
Speed	•	•	•	•
Efficiency		•	•	
• Indicates condition monitoring measurement parameter applicable				

ISO 10816 suggests that alarm- and trip limits are implemented for long-term operations [101]. A warning should be generated when an alarm limit violation occurs. The warning notification should be investigated within a predetermined period. A trip limit, however, specifies a maximum allowable threshold. Operating above this limit may cause damage to the equipment.

Warning notifications can help identify a developing fault. Table 2.5 shows typical fault-symptom relationships for large fans [104]. For example, a change in speed may indicate that the impellar is damaged. Corresponding tables can be obtained for pumps, compressors and electric motors.

Table 2.5: *Fault symptoms for industrial fans* [104]

Fans	Symptom or parameter change									
Fault	Air leakage	Length measure-ment	Power	Pressure	Speed	Vibration	Temper - ature	Coast down time	Oil debris	Oil leakage
Damaged impellar		•	•	•	•	•	•	•	•	
Damaged oil seals		•		•	•				•	•
Damaged bellows	•									
Eccentric impeller			•	•	•	•	•	•		
Bearing damage		•	•		•	•	•	•	•	•
Bearing wear		•				•	•	•	•	
Mounting fault						•				
Rotor fouled						•				
Unbalance						•				
Misaligment		•				•				
• Indicates symptom may occur or parameter may change if fault occurs										

Asset health

Various methods and strategies have been developed to evaluate the operational condition, or health status, of machinery. Condition monitoring information can be used to determine whether an asset's health has deviated from what is considered to be normal [78]. The aim is therefore to identify failure symptoms and evaluate the corresponding parameters. Limited literature is available regarding asset health in an underground mining environment. However, case studies on industrial equipment provided insight into possible condition monitoring techniques for deep level mine equipment.

Vibration measurements have been shown to be effective health indicators [44], [53]. Abu-Zeid and Abdel-Rahman [35] demonstrated how defective bearings cause an increase in both the vibration amplitude and the power consumption. After replacement, the vibration level (RMS) decreased from 4.5 mm/s to 0.7 mm/s. The study shows that the identification of a defect can lower the operating and maintenance costs on a pump.

Other studies have also shown that RMS and peak values of vibration-based signals are good indicators of equipment condition. Jayaswal *et al.* [56] observed that vibration RMS values can be used to evaluate bearing conditions. Igba *et al.* [105] proved that RMS and peak values are good indicators of a wind turbine's gearbox health. Progressive failures, such as bearing pitting, were detected a month before the functional failure.

Touret *et al.* [106] discusses how gears and bearings generate vibration, debris and heat whilst failing. The authors note that, although vibratory and debris analyses are proven condition monitoring approaches, temperature monitoring can be considered to be a definite alternative. By analysing gearbox temperatures it is possible to detect defects such as bearing spalling, bearing misalignment and lubrication losses [106].

Berge *et al.* [42] developed a technical condition index to describe the state of degradation of a wastewater pump. The methodology was implemented on a pumping station where the results from the analyses were made available to the pump station operators. The authors stated that temperature and vibration parameters are key indicators of a pump's condition.

In terms of the best maintenance strategy to implement, the choice is far from trivial [94], [107]. Relevant information is needed to describe the failure process and to optimise the time between preventative maintenance actions. A maintenance approach consisting of only preventative or corrective activities leads to inefficient use of manpower, extended equipment downtime and, ultimately, loss of revenue [43]. Maintenance decisions can be improved by exploiting deterioration and process data to serve as system health indicators [45], [36]. Preventative maintenance intervals for mining equipment can be optimised by evaluating trends in the equipment operating characteristics [46].

CBM makes it possible to schedule future preventative maintenance [9], while time-based maintenance techniques that make use of periodic intervals, may cause unexpected and unnecessary shutdowns [100], [44]. Condition monitoring systems have a positive impact on equipment uptime, mean time between maintenance, production rates and the overall operation effectiveness (OOE) [108]. Knowledge of failed components enables targeted repairs, instead of trial-and-error campaigns [108].

Failure prediction and life estimation of integrated systems is an exceedingly difficult task for researchers and engineers [109]. The state of its critical components directly influences the capability of machinery to sustain its required function without failure [109]. Automation systems typically have ample measurement information available, which could be utilised for diagnostics and prognostics of the machine condition [109]. Associated benefits of the CBM approach include reduced maintenance costs, improved reliability and availability, increased equipment lifetime and enhanced operator safety [44], [55].

2.4 Summary

Unplanned maintenance results in equipment downtime, as well as high repair costs that might have been avoided. Deep level mines are under pressure to remain profitable, and therefore need to lower their operational costs. An information system can facilitate remote CBM on deep mines. This would enable maintenance supervisors to investigate operational risks before they are critical, and schedule service repairs where necessary.

Equipment health analysis models, which are based on various types of methodologies and mathematical techniques, have been researched. Although promising, these methods are very complicated, at times require specialist software and have little evidence of practical feasibility, especially in the mining sector. Industrial manufacturing solutions are not a viable option, since they require high capital expenditure. A need therefore exists for a simplified monitoring approach that uses existing infrastructure and be implemented within a mining environment.

Literature has shown that vibration and temperature parameters have been used successfully to determine the operational health of machines and systems. Bearings are related to a large portion of equipment failures, which is why it is recommended for them to be monitored. Operational risks, or failure symptoms, can be identified by continuously monitoring a range of equipment parameters. This information can subsequently be used to develop a CBM strategy. CBM has shown to reduce operational and maintenance costs, while promoting a safer working environment.

CHAPTER 3

Data acquisition and preparation

3.1 Preamble

Large quantities of compressed air, cold water and ventilation are needed to enable mining operations to be efficient and safe. High-pressure compressed air is supplied to pneumatic drills used on underground levels. Cold water is used for cooling while these drills are operational. The water is supplied by refrigeration machines and is used by spot coolers or cooling cars, as well as BACs for ventilation purposes. Mine ventilation systems maintain the underground air temperature and humidity. The ventilation fans also extract harmful blasting fumes and exhaust emissions from machinery. Used water is collected in underground settlers before pumps on various levels are used to pump the water back to the surface. This process is known as mine dewatering.

In order to effectively monitor these systems, it is necessary to continuously analyse the relevant machine- and process data. The aim of a holistic assessment would not only be to analyse individual parameters or selected equipment, but the systems and operation as a whole. Figure 3.1 shows an overview of a mining operation with the respective systems that will be analysed.

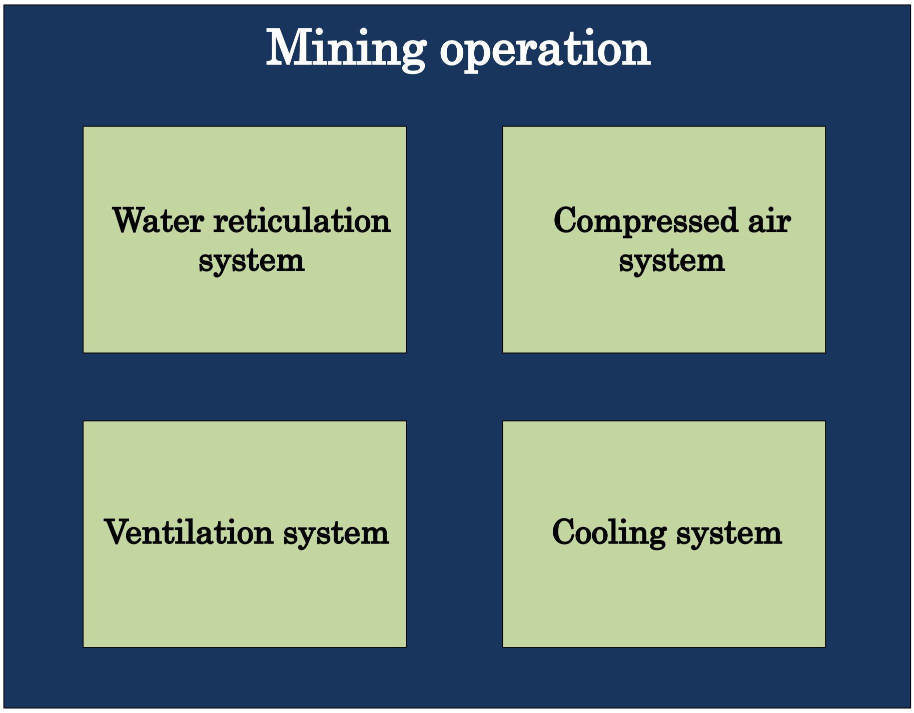


Figure 3.1: *Overview of mining operation systems*

Each system depicted in Figure 3.1 consists of several subsystems. Figure 3.2 shows an example of a water reticulation system, which consists of several pumps, located on different levels. Key parameters to be analysed are selected for each system. Figure 3.3 shows the bottom level of the analysis tree. Example parameters include pump- and motor vibrations, as well as drive end (DE) and non-drive end (NDE) bearing temperatures. Each pump is therefore analysed individually. Corresponding pumps can then be grouped together to obtain a level-specific analysis and, finally, a water reticulation system analysis. The same procedure is followed for the remaining systems.

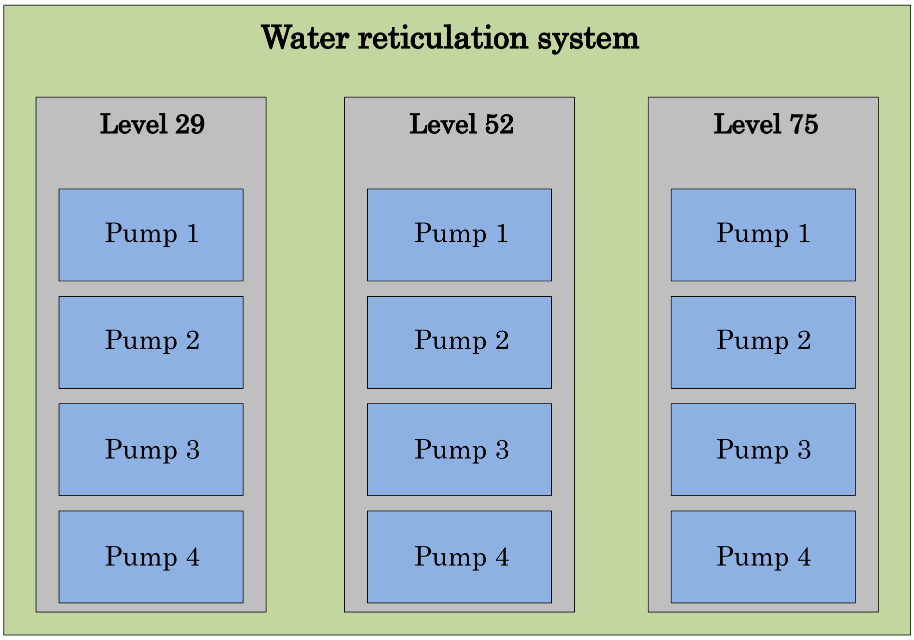


Figure 3.2: *Example of a water reticulation system*

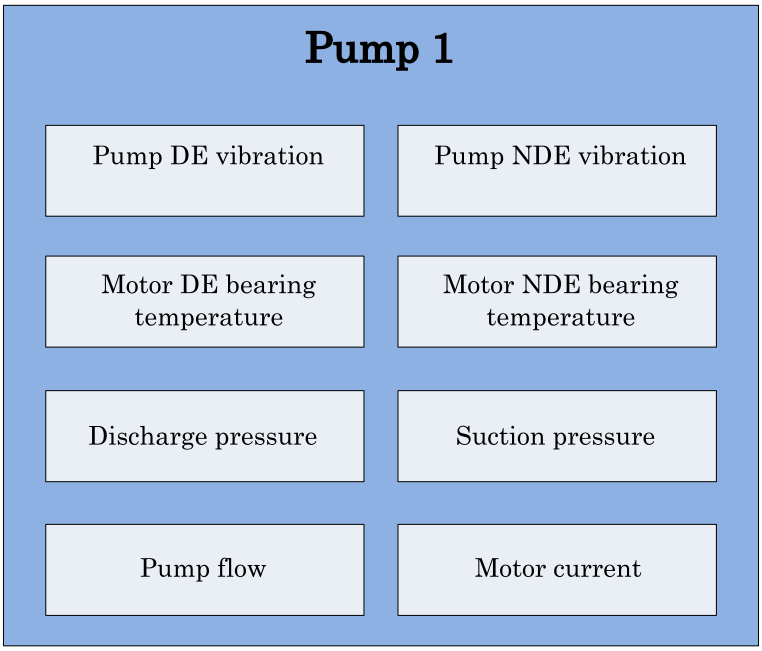


Figure 3.3: *Example parameters for pump analysis*

3.2 Subsystem overview and requirements

Figure 3.4 shows the design elements that will be discussed in this chapter. The first module includes the gathering, combining and structuring of data. The process of data transfer from an industrial site server to a localised analysis server relates to the second module. The third module comprises the data translation specifications.

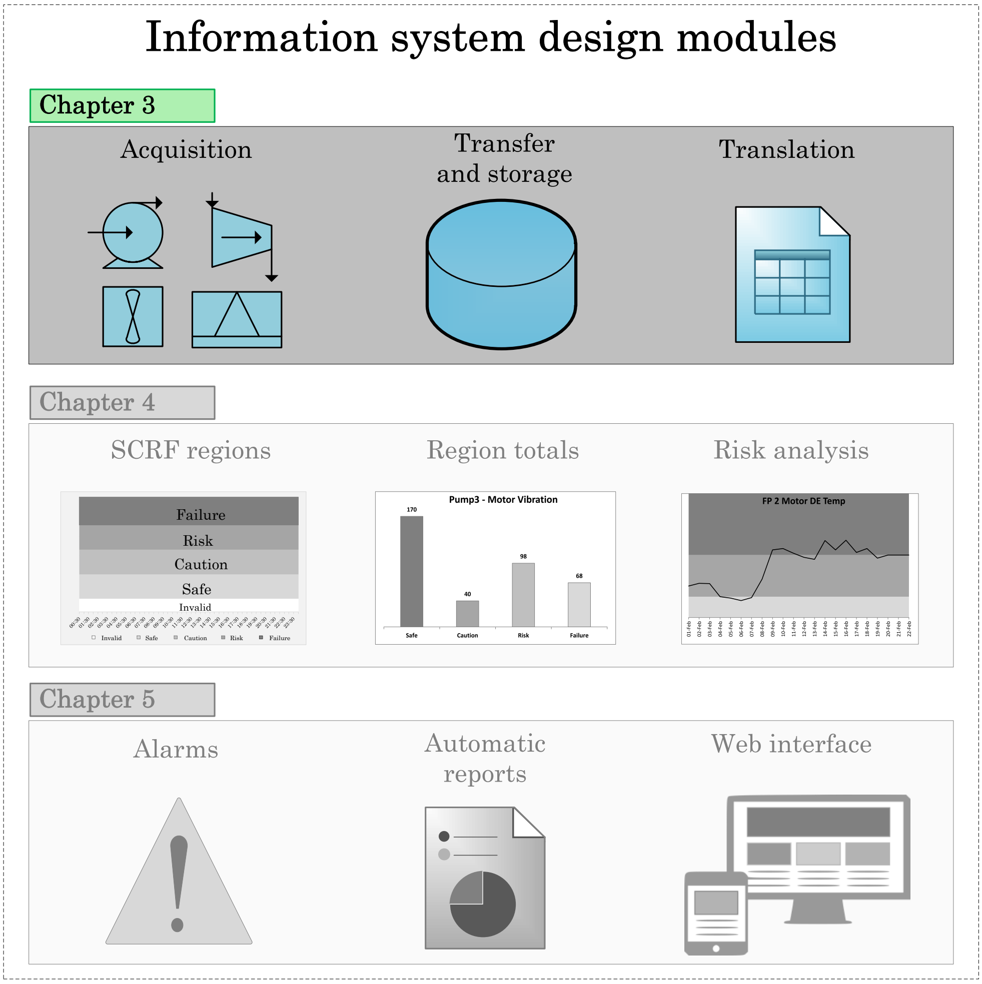


Figure 3.4: *Overview of Chapter 3 design elements*

The field of data science (data processing and analysis) has grown exponentially during the past decade. The concept of big data has become a fundamental part of data analytics. Big data was initially introduced as having three dimensions, namely volume, variety and velocity [110]. Volume refers to the amount of data and can range from megabytes to petabytes. Variety refers to the different types of data being analysed. Velocity refers to the interval of newly generated data and the sampling rate thereof.

The data acquisition process of the information system needs to be automatic, due to the variety and velocity of condition monitoring data. It is also necessary that a data preparation functionality is incorporated into the process of data collection. Condition monitoring data is logged and stored on a remote server (located on site). These log files must, however, be sent to a local server, which is situated at the ESCO office. This is done via email and therefore has an internet service provider (ISP) fee associated with it. Larger log files will result in a higher ISP data usage cost.

Data aggregation can be used as a form of pre-processing. Two-minute interval samples can be aggregated to half-hourly averages. This translates sets of 15 samples, or data points, into a single value. A trade-off is therefore made between data resolution and file size. Fewer data points do however reduce processing time and ISP expenditures. It was therefore decided that 48 daily samples (30-minute averages) per parameter will be used for the analysis.

Taking these considerations into account, it was determined that the requirements, or functional specifications, include the following:

- Raw data files containing two-minute interval data (720 values) should be stored on the remote server.
- 48 aggregated values must be calculated for each of the parameters being logged.
- The data logger should give the user the option to log selected parameter values only if a preset condition is true.
- The option for log files to be compiled on a daily basis (thus a single log file with 48 time intervals), or on a half-hourly basis (thus 48 separate log files, each containing a single time interval).
- Log files must be compiled and automatically sent to the local server.
- The data translation system should link the SCADA tag values to a local database tag and automatically populate the respective database tables upon reception of new log files.
- The data translation system must be able to extract data of selected parameters from the local database for a date range specified by the user.

3.3 Design detail and development

The information system was designed to analyse data on a daily basis and to identify any risks within the respective systems. Another specification of the system was to receive and translate data on a half-hourly basis. This would provide the user with a near real-time view of the current state of the system. A data logger was therefore designed and developed to implement these specifications. An existing data translation system was used to add values to the database and to create the relevant input sheets.

Data acquisition

A SCADA system localises the data obtained from equipment and systems on a mining site. ESCOs make use of an Open Platform Communications (OPC) server to acquire relevant energy data from the SCADA. The OPC connection enables an ESCO to create a communication link between their Energy Management System (EMS) and the mine's SCADA.

An existing EMS was used to facilitate the process of data collection. A new data logger was developed and added to the list of available components on the EMS interface. The new logger was designed to enable the user to specify a condition and link it to selected parameters. These parameter values will consequently be logged only if the condition holds true. A tag operation type and interval can also be specified by the user. Operation types include maximum, minimum, average or total. The two time-interval options are daily and half-hourly. Figure 3.5 illustrates how these logging options can be implemented.

Conditions	
Name	Description
Pump2_Running	Pump2_Power > 0
FP1_GuideVane	FP1_GuideVane > 95
Comp3_Running	Comp3_Power > 0

Example log 1	
Parameter	FP1_CoolingDuty
Operation interval	30 minutes
Operation type	Average
Condition	FP1_GuideVane

Example log 2	
Parameter	Pump2_DE_Vibration
Operation interval	30 minutes
Operation type	Maximum
Condition	Pump2_Running

Example log 3	
Parameter	Pump3_Trips
Operation interval	Daily
Operation type	Total
Condition	–

Figure 3.5: *Example of conditional logging specifications*

The list of parameters that have been added to the logger component will be logged and aggregated according to the settings configuration. A raw log, containing two-minute interval entries, is saved on the remote server. The raw log can then, for example, be used to calculate the half-hourly averages. These log files are compiled in a *comma separated values* (CSV) format. CSV files only contain plain text and can therefore be edited by almost any spreadsheet application or text editor. In addition to this, these files can be compressed to reduce the file size.

The output file of a 30-minute average configuration will therefore comprise 48 values per parameter. Figure 3.6 shows the generic layout of an output file. Subscript m is the total number of time intervals, while subscript n is the number of components. The number of parameters are indicated by i, j and k. $C_nP_kV_m$ therefore refers to the value of parameter k, belonging to component n at time interval m.

Time	Tag	Value
T_1	C_1P_1	$C_1P_1V_1$
T_1	C_1P_2	$C_1P_2V_1$
T_1	C_1P_i	$C_1P_iV_1$
T_1	C_2P_1	$C_2P_1V_1$
T_1	C_2P_2	$C_2P_2V_1$
T_1	C_2P_j	$C_2P_jV_1$
T_1	C_nP_1	$C_nP_1V_1$
T_1	C_nP_2	$C_nP_2V_1$
T_1	C_nP_k	$C_nP_kV_1$
$\vdots$	$\vdots$	$\vdots$
T_m	C_1P_1	$C_1P_1V_m$
T_m	C_1P_2	$C_1P_2V_m$
T_m	C_1P_i	$C_1P_iV_m$
T_m	C_2P_1	$C_2P_1V_m$
T_m	C_2P_2	$C_2P_2V_m$
T_m	C_2P_j	$C_2P_jV_m$
T_m	C_nP_1	$C_nP_1V_m$
T_m	C_nP_2	$C_nP_2V_m$
T_m	C_nP_k	$C_nP_kV_m$

Figure 3.6: *Generic layout of log files*

The data logger also gives the user the option to specify a log schedule interval. This schedule determines how often a new output file is generated. Considering a 30-minute average configuration and selecting a 24-hour log schedule will result in a single daily log file with 48 time intervals. Correspondingly, a 30-minute log schedule will result in 48 daily log files, each consisting of only one time interval. Receiving log files every 30 minutes allows personnel to remotely monitor the current state of the respective mining systems, without being on site.

Figure 3.7 graphically displays how the logging process works and how the output files are created. Multiple loggers can therefore be used to obtain different types of calculations for use in the analysis process.

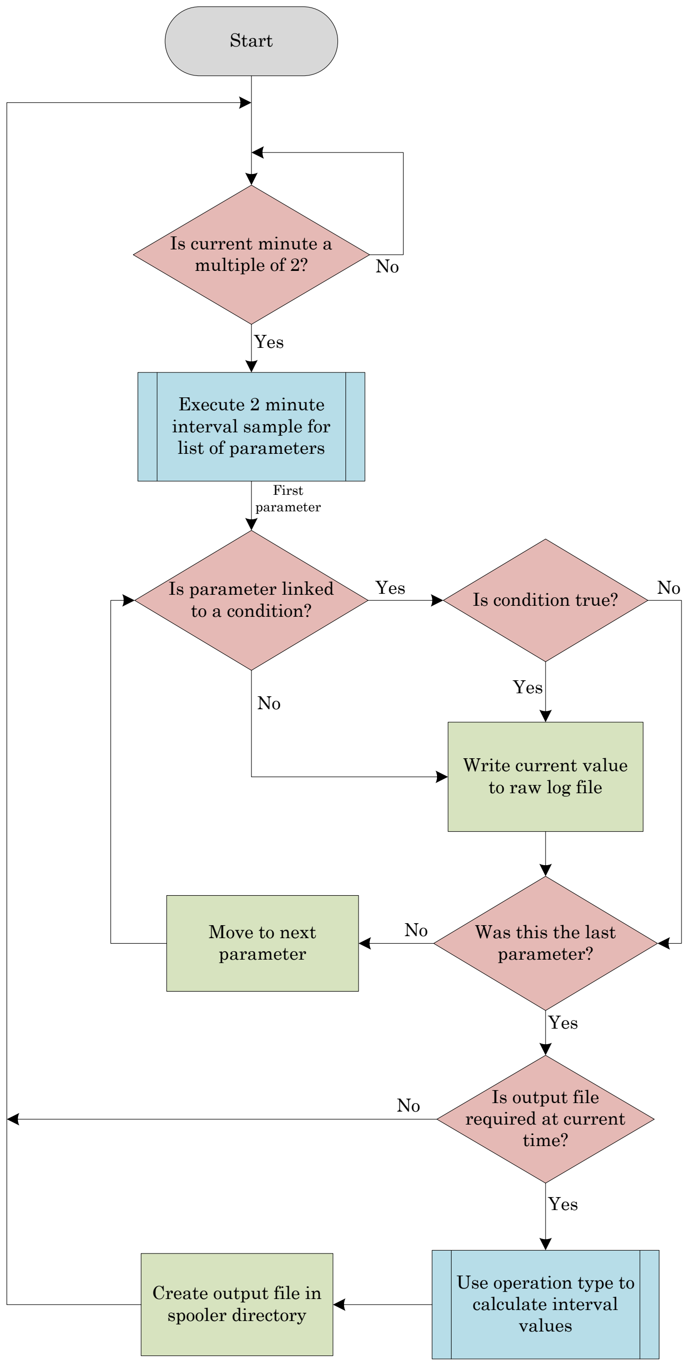


Figure 3.7: *Data logging process*

Data transfer and storage

Log files can be used for analysis once the parameters and corresponding tag operations have been configured on the respective data loggers. Log files are generated according to the selected schedule interval. These log files (containing the relevant machine- and process data) are stored on remote servers, located on the respective mining site. Data must therefore be sent from the remote servers to a centralised local server, located at the ESCO head office, before it can be processed. The parameter values must also be added to a database in order for it to be displayed on the web interface. Data will also be extracted from the database when performing a daily, weekly or monthly analysis. The entire data transfer and storage process needs to be automated.

Data transmission is made possible by using a secure communication channel. A private access point name (APN) connection can be established by making use of a mobile network router [24]. An existing virtual private network (VPN) can also be used if the use of a router is not permitted by the mine. These routers make use of a mobile subscriber identification module (SIM) card, which can be loaded with a mobile data bundle. Application-specific software has been developed to send energy data via email by using this communication method. An existing software application was reconfigured to send condition monitoring data to a local server at regular intervals.

Figure 3.8 illustrates how the communication configuration is set up. A simple mail transfer protocol (SMTP) service is used to transfer data from the EMS server to the local server. The EMS server can also be accessed remotely (via the mobile network routers and a private APN) to view and retrieve raw log files. The mail application is used to send compiled log files (output files with 30-minute aggregated values) on a half-hourly basis. These log files are sent as a single attachment to a predefined email address.

Once received, the translation system will process the email and attachment. The incoming emails are distributed to the relevant mining group directory. Emails are sent with an attachment that contains the data logs of the respective systems. Selected parameter values for the relevant time interval are compiled in system-specific log files. The entries of these log files can subsequently be added to the database.

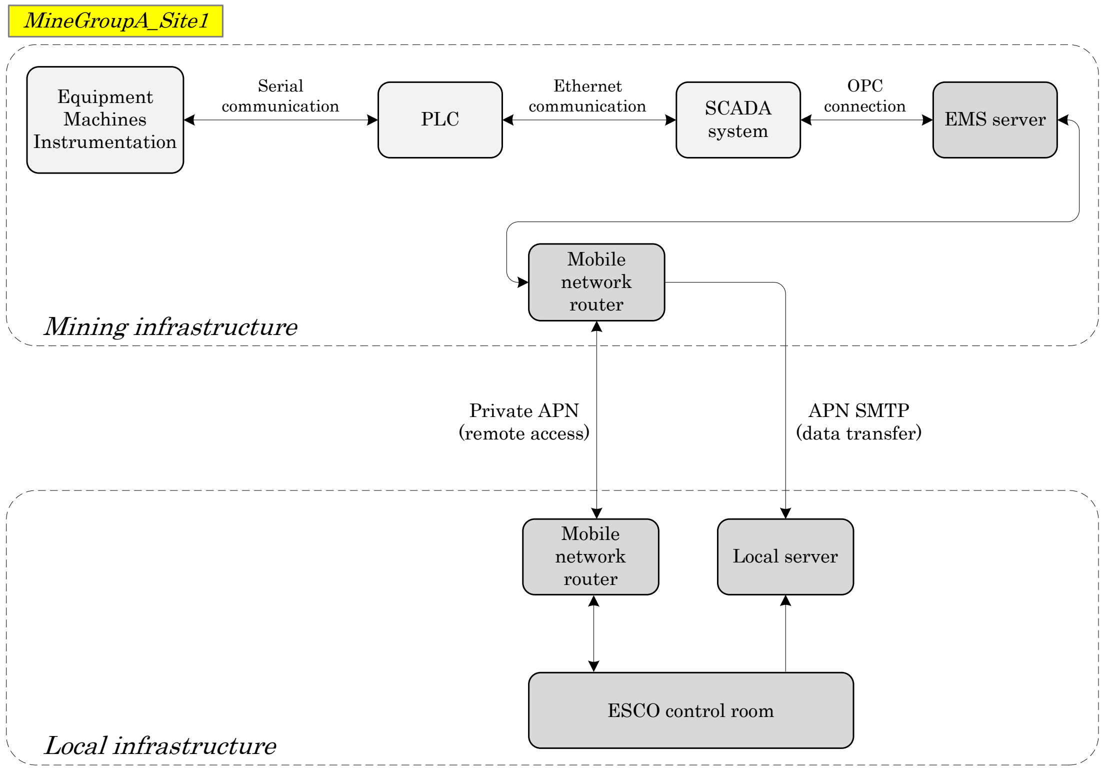


Figure 3.8: *Remote site communication configuration* (adapted from [24])

Figures 3.9 and 3.10 show an example of the data transfer process. Log files are compiled and sent to a spooler folder (temporary folder) every 30 minutes. The mailing application can be been configured to email the contents of the spooler folder to a group-specific email address. These emails are sent two minutes after each half-hour interval (Figure 3.9). Such a configuration can be implemented on sites from different mining groups. Emails from various mining groups and sites are therefore received every 30 minutes and sorted accordingly (Figure 3.10).

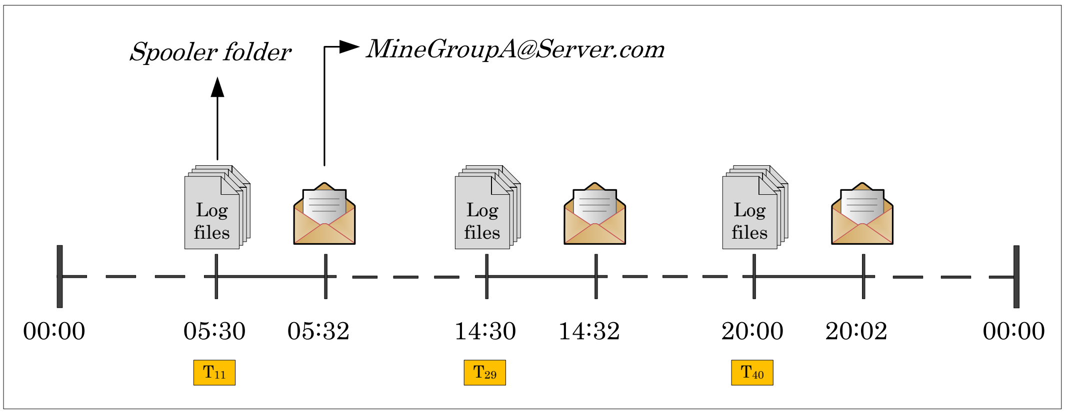
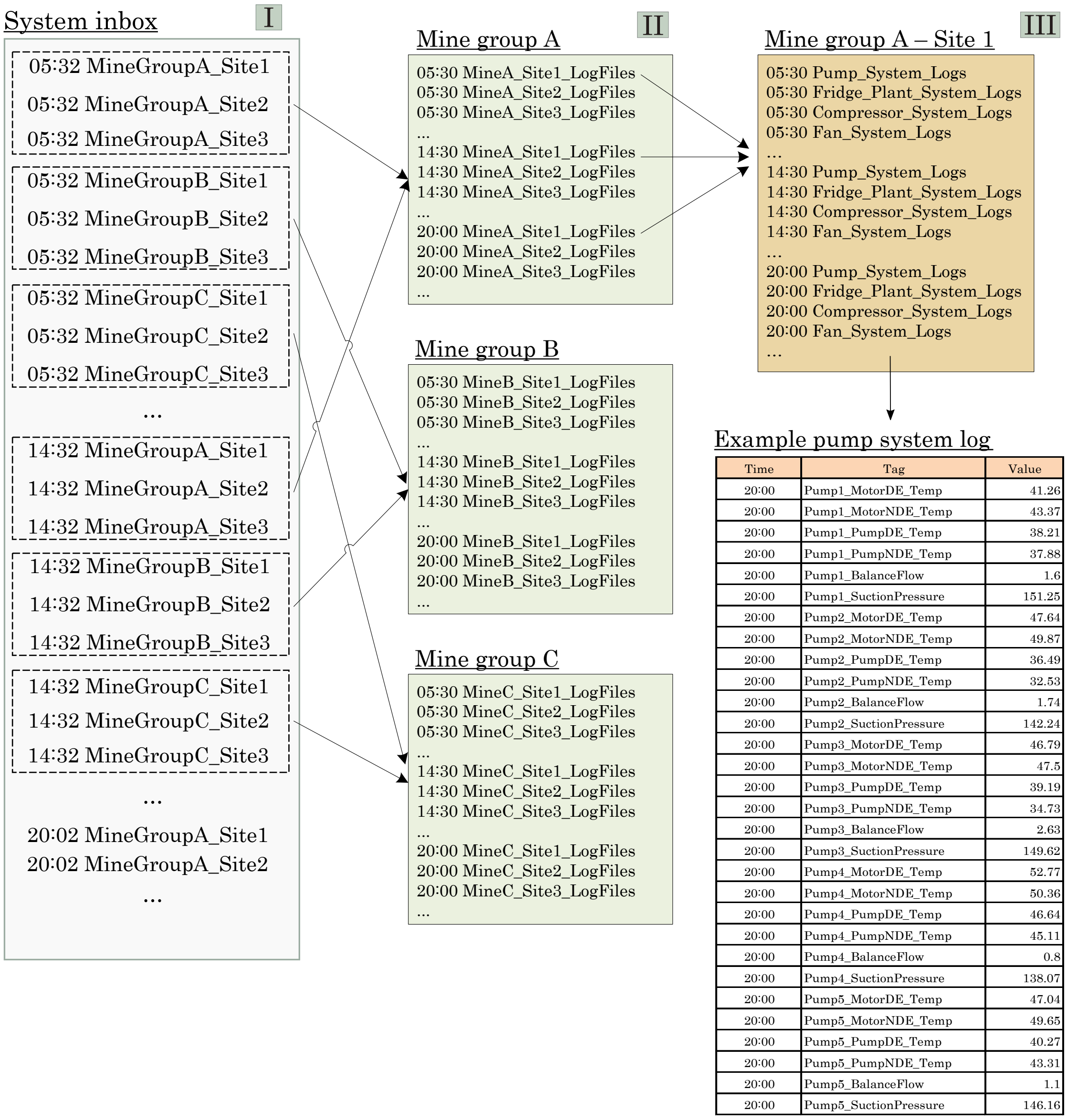


Figure 3.9: *Example of data transfer interval*



Time	Tag	Value
20:00	Pump1_MotorDE_Temp	41.26
20:00	Pump1_MotorNDE_Temp	43.37
20:00	Pump1_PumpDE_Temp	38.21
20:00	Pump1_PumpNDE_Temp	37.88
20:00	Pump1_BalanceFlow	1.6
20:00	Pump1_SuctionPressure	151.25
20:00	Pump2_MotorDE_Temp	47.64
20:00	Pump2_MotorNDE_Temp	49.87
20:00	Pump2_PumpDE_Temp	36.49
20:00	Pump2_PumpNDE_Temp	32.53
20:00	Pump2_BalanceFlow	1.74
20:00	Pump2_SuctionPressure	142.24
20:00	Pump3_MotorDE_Temp	46.79
20:00	Pump3_MotorNDE_Temp	47.5
20:00	Pump3_PumpDE_Temp	39.19
20:00	Pump3_PumpNDE_Temp	34.73
20:00	Pump3_BalanceFlow	2.63
20:00	Pump3_SuctionPressure	149.62
20:00	Pump4_MotorDE_Temp	52.77
20:00	Pump4_MotorNDE_Temp	50.36
20:00	Pump4_PumpDE_Temp	46.64
20:00	Pump4_PumpNDE_Temp	45.11
20:00	Pump4_BalanceFlow	0.8
20:00	Pump4_SuctionPressure	138.07
20:00	Pump5_MotorDE_Temp	47.04
20:00	Pump5_MotorNDE_Temp	49.65
20:00	Pump5_PumpDE_Temp	40.27
20:00	Pump5_PumpNDE_Temp	43.31
20:00	Pump5_BalanceFlow	1.1
20:00	Pump5_SuctionPressure	146.16

Figure 3.10: *Example of email reception*

As shown in Figure 3.10, emails are moved from the system inbox to the relevant mine group directory (from I to II in Figure 3.10). Only selected time intervals are shown in the diagram to simplify the illustration. There will, however, be 48 emails per day for each site. The system-specific log files are extracted and added to the relevant site's processing folder (from II to III in Figure 3.10). A data processing procedure is performed each time that files are added to a site's processing folder. This procedure imports the received values to the system database.

The log file entries are used to create local database tags. The data processing procedure will therefore try to match incoming data with the list of available database tags. The incoming values will then be added to the relevant data tables of the respective database tags. An existing database (containing mostly energy-related data) was modified and expanded to accommodate the condition monitoring data. New data tables were therefore created to structure and organise the data.

Various database management systems (DBMS) are available for commercial applications. DBMS vary in cost and functionality [27]. DBMS features that need to be considered are the maximum allowable database size, as well as security. MySQL Community Edition[1] is an open source database (free of charge) and is available under a General Public Licence (GPL). This gives users the option to modify the software according to their specific application requirements [111]. The allowable database size is also unlimited when using MySQL. Having considered these features, MySQL was chosen for a DBMS.

Figure 3.11 shows a segment of the entity relationship diagram (ERD) of selected database tables. Each of the tables have a primary key (PK), which can consist of single or multiple fields. PKs are used in relational database tables as unique identifiers. Each mining project can be linked to different types of equipment. A specific pump or compressor can, however, only be associated with a single project.

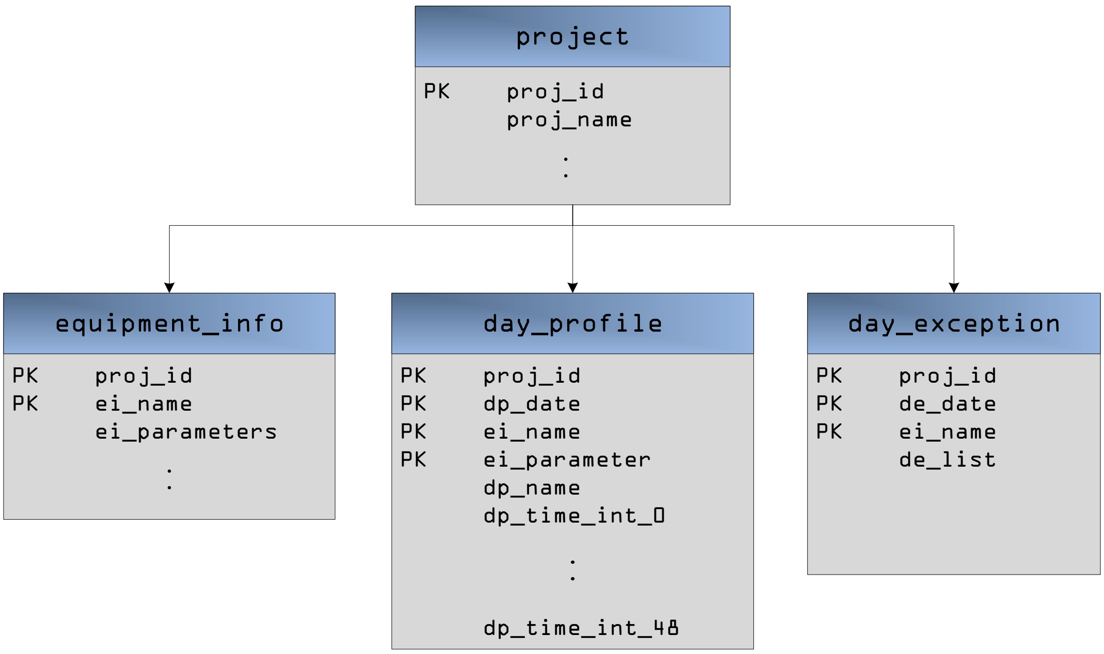


Figure 3.11: *Partial ERD of the database*

[1]Oracle Corporation – https://www.mysql.com/products/community/

Half-hourly process data is stored in the corresponding *day_profile* table. The *day_profile* table has a composite PK consisting of the project identifier, date, equipment identifier and specific parameter. Exception parameters (where risks have been identified) can then be stored in the *day_exception* table. Process and exception data, from various mining sites are therefore centralised and can be readily viewed on a web interface.

Data translation

Data analysis procedures require input data in a predefined format. Selected parameter data, for a specified date range, must be extracted from the database and translated into a usable format. Automated reports can be developed to analyse raw data and compile system-specific information. The raw data must therefore be made available on an input sheet before the results from the analysis can be exported to an output, or report, sheet. The report sheet can then be sent to a list of recipients.

A data translation system, developed by an ESCO for energy reports, was used to prepare the necessary process data for analysis. The system allows a user to link database tags to an automated report. Reports can be configured to be generated on a daily, weekly or monthly basis. The user must also specify how many days' data should be extracted from the database upon generation of the report. A pump analysis, pertaining to data from the past 10 days, can therefore be performed on a daily basis.

A report is added to the processing list once a user has completed a new report setup. Figure 3.12 illustrates the preparation process of a report's input sheet. This process is executed on a daily basis. Some reports (e.g. a monthly report) are therefore only generated on selected days. Each report's input sheet is populated according to its linked tags and selected data interval. The report's analysis script is executed once the input sheet preparation has been completed.

This process was followed to create system-specific reports and an exception report. The system-specific reports were created to analyse four mining systems (water reticulation, compressed air, ventilation and cooling) individually. The exception report summarises risks that were identified on these four systems.

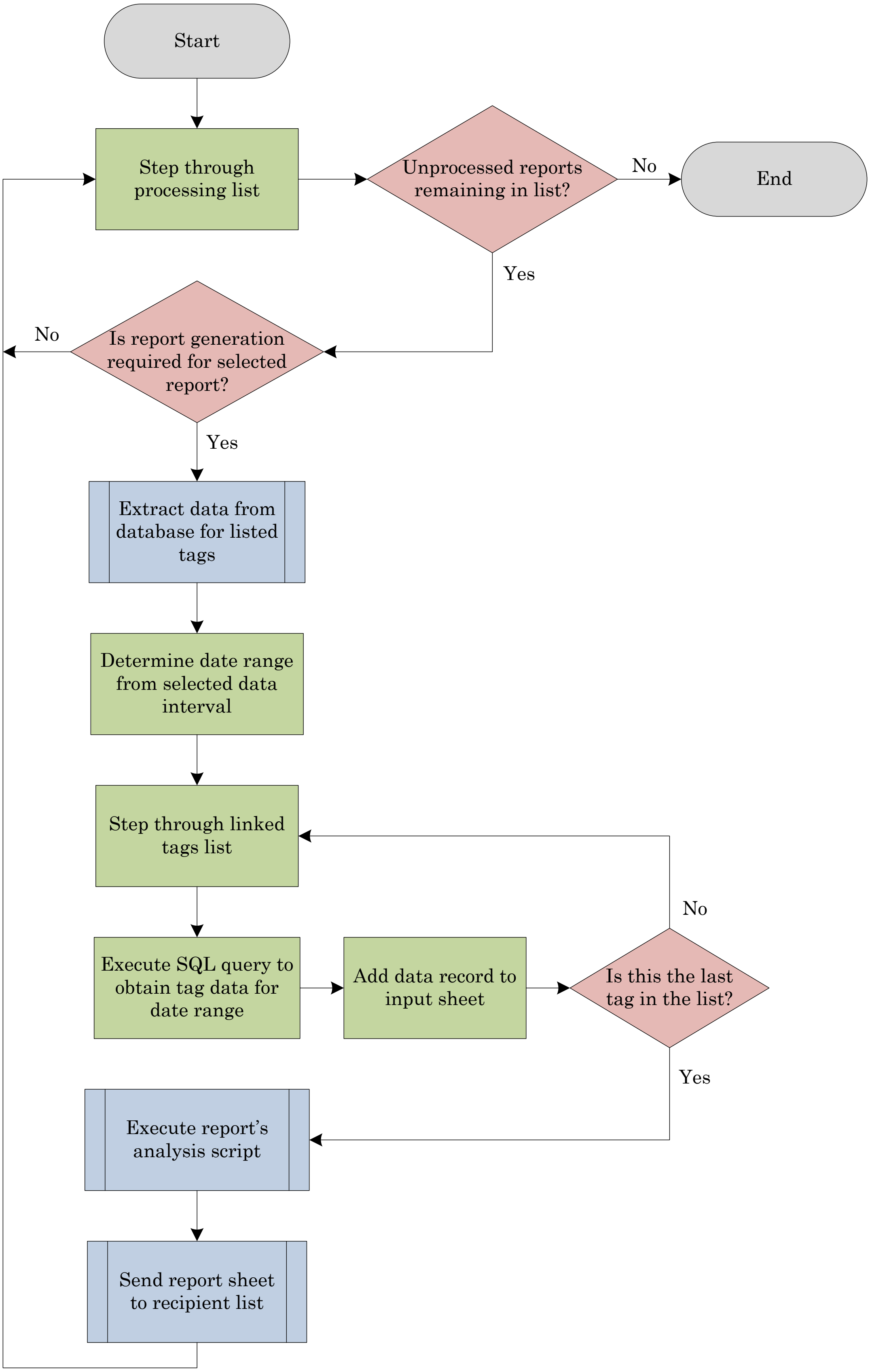


Figure 3.12: *Input sheet preparation process*

Figure 3.13 shows a data record example of a pump temperature tag. The values were logged as half-hourly averages. Section A of the record contains information relevant to the specific tag. The *Tag ID* field is a unique identifier and is assigned to each tag when it is added to the database. The *Tag Source* field refers to the source of the tag data, i.e. log files, electricity bill, etc. The *Tag Unit* refers to the unit of measurement and must be specified when the tag is created. The *Tag Name* is also a unique identifier and should preferably contain the mine group name, specific site name, component name and parameter type.

The content of section B is determined by the relevant tag type. A 48-sample tag will have 48 intervals, while a daily or a monthly tag will only have a single interval. Section C contains the tag data for the selected date range. The report associated with the example data record was configured to include seven days' data.

Tag ID:	2512						
Tag Source:	9						
Tag Unit:	deg C						
Tag Name:	MineA_Site1_Pump1_MotorDE_Temp						
Date:	02-Jan	03-Jan	04-Jan	05-Jan	06-Jan	07-Jan	08-Jan
00_30	40.26	39.87	38.24	40.49	38.78	41.47	43.86
01_00	40.09	39.94	38.35	40.4	38.79	41.08	43.61
01_30	39.92	40	38.37	40.15	38.88	40.91	43.12
02_00	39.92	40.12	38.48	38.54	39.06	40.85	43.03
...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...
22_30	40.71	42.03	42.37	40.33	45.8	46.4	45.21
23_00	40.47	41.55	41.82	40.15	45.15	45.9	44.85
23_30	40.11	41.07	41.46	40.09	44.45	45.41	44.5
24_00	39.94	40.62	41.32	40.01	44.03	44.97	44.13

Figure 3.13: *Example of input sheet data record*

3.4 Module verification

The requirements listed in the functional specification were used to perform the verification of the *Data acquisition and preparation* subsystem. Each requirement was verified with multiple datasets. Names of mining sites were generalised due to confidentiality agreements.

The subsystem was subjected to a form of stress testing to verify its functionality. More than 300 tag parameters were added to the logger component. The compiled log files and processing thereof were monitored for a period of 30 days. Table 3.1 lists some relevant figures regarding the verification of the data acquisition process.

Table 3.1: *Verification of data acquisition*

Description	Count
Number of parameters	316
Raw log samples per parameter	720
Total entries in daily raw log file	227 520
Output file samples per parameter	48
Total entries in daily output file	15 168
Number of days in verification period	30
Log entries processed in verification period	455 040

Parameter values are written to the raw log file every two minutes. The raw log file is kept on the remote server due to the large file size. Figure 3.14 shows an example of two parameters' raw data. These raw log values are subsequently used by the logger component to create 48 aggregated values (according to the operation type) and compile the required output file.

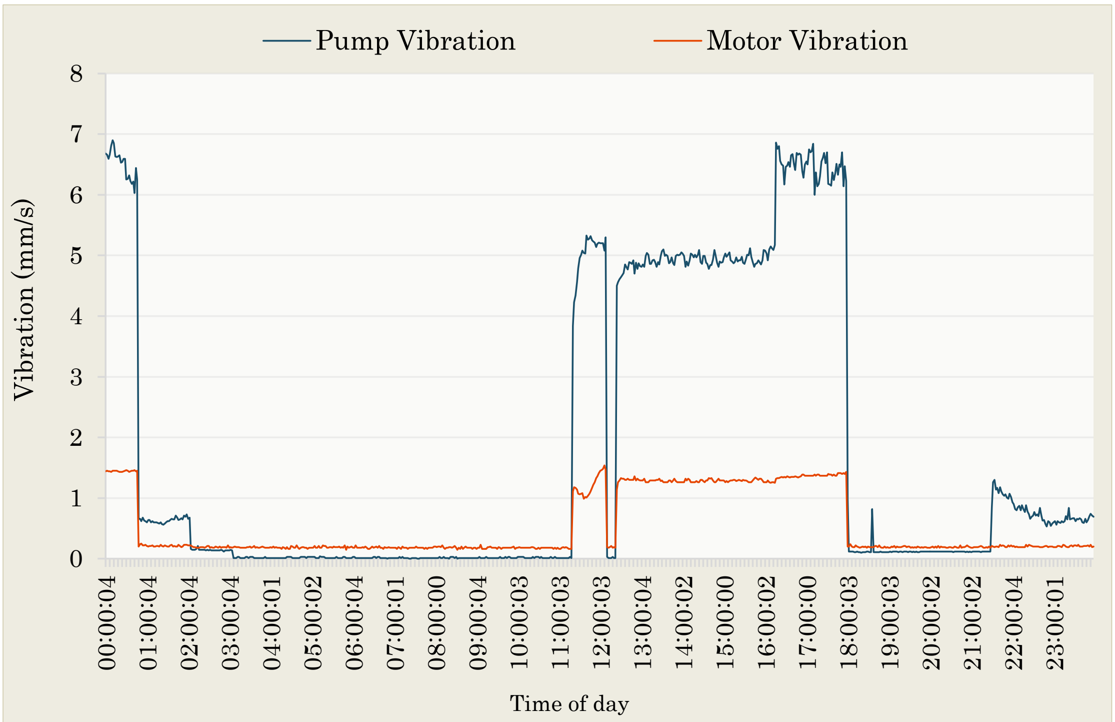


Figure 3.14: *Pump vibration raw data*

These pump parameters (shown in Figure 3.14) were added to two separate logger components to verify the aggregation calculations. One logger was configured to calculate half-hourly averages, while the second logger was configured to calculate half-hourly maximums.

Figure 3.15 shows the result of the average operation type, while Figure 3.16 shows the result of the maximum operation type.

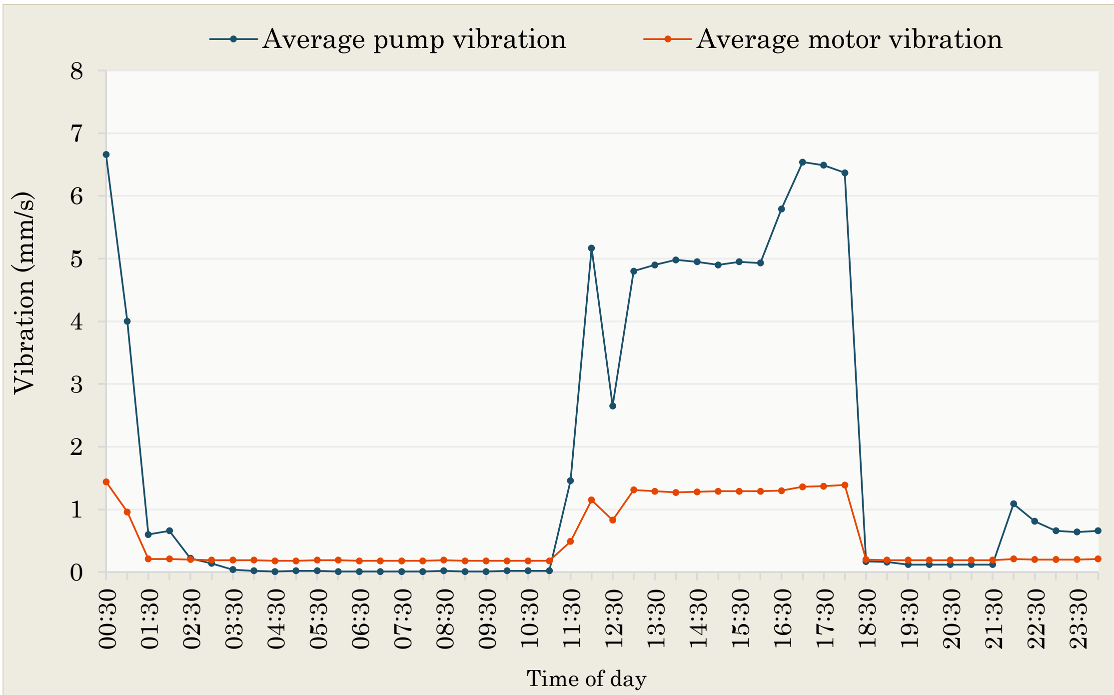


Figure 3.15: *Pump vibration average data*

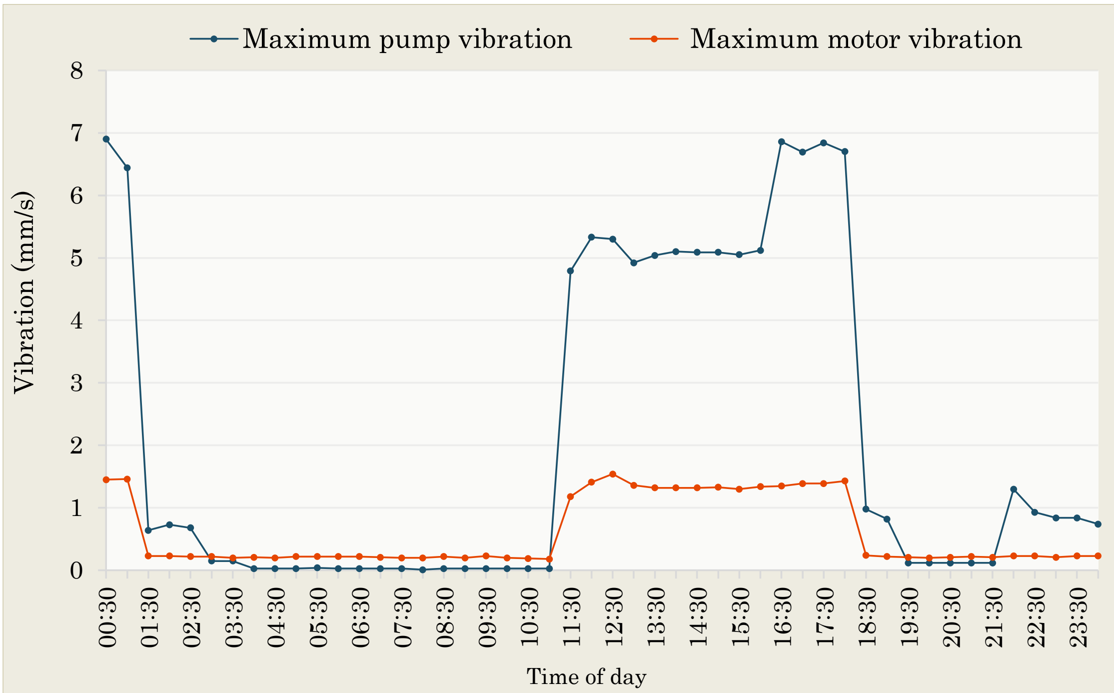


Figure 3.16: *Pump vibration maximum data*

The aggregated data's representation of the original input signal was judged to be acceptable. For the purposes of this application the reduced data resolution would therefore not have a significant impact on the analysis.

The option to specify logging conditions, which need to be satisfied before the respective tag values are added to the log file, was also listed in the requirements of the functional specification. Conditional logging was used to determine pump flow averages. In some cases only the total column flow is available, where the column flow might consist of several pump flows. The average flow of a specific pump can therefore only be calculated when no other pumps are contributing to the total flow. This was accomplished by creating a flow condition for each pump. The logger will consequently assign the total flow to the relevant pump's average flow, if the corresponding flow condition is satisfied.

Figures 3.17, 3.18 and 3.19 demonstrate another implementation of conditional logging. Pump- and motor temperature values were logged only if the pump's running status was *ON*. This enables the user to calculate a running average of the pump parameters. A running average provides a better representation of the equipment's operational condition.

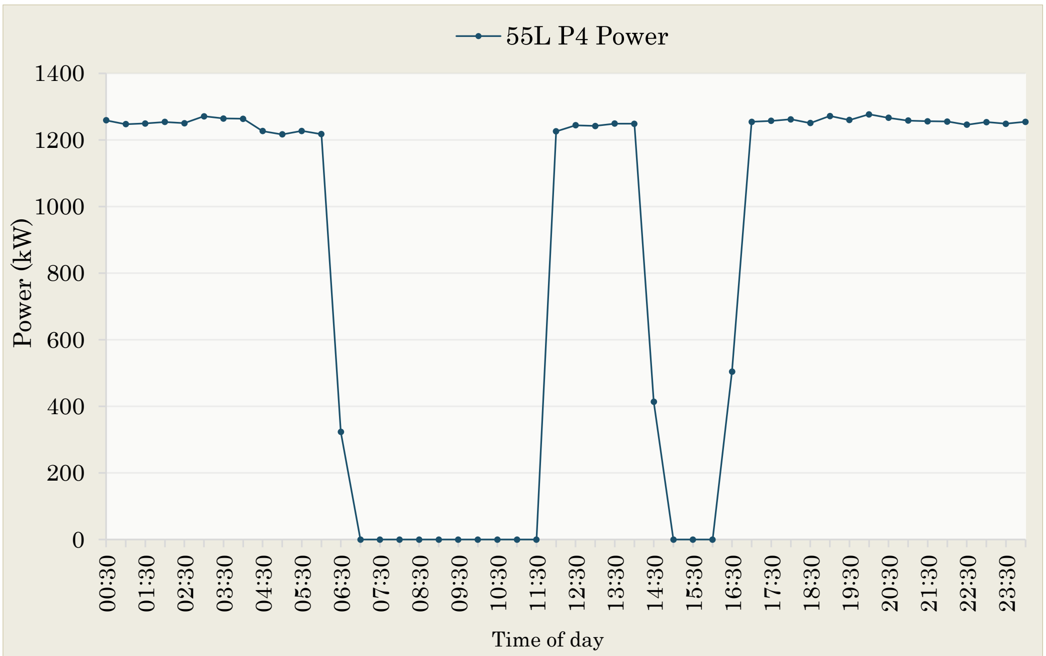


Figure 3.17: *Pump power data used for conditional logs*

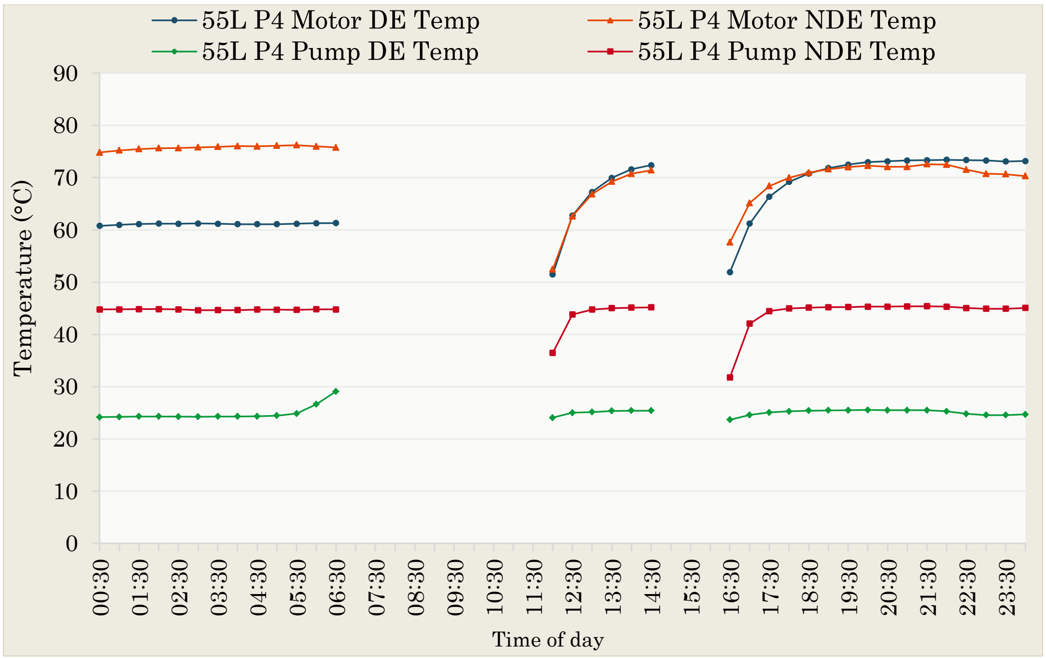


Figure 3.18: *Conditional logging of temperature data*

Figure 3.18 shows that half-hourly averages are only calculated during the pump's operational periods. These values can therefore be used to calculate daily averages. Figure 3.19 shows a comparison between the daily averages of values logged with a condition, as well as without.

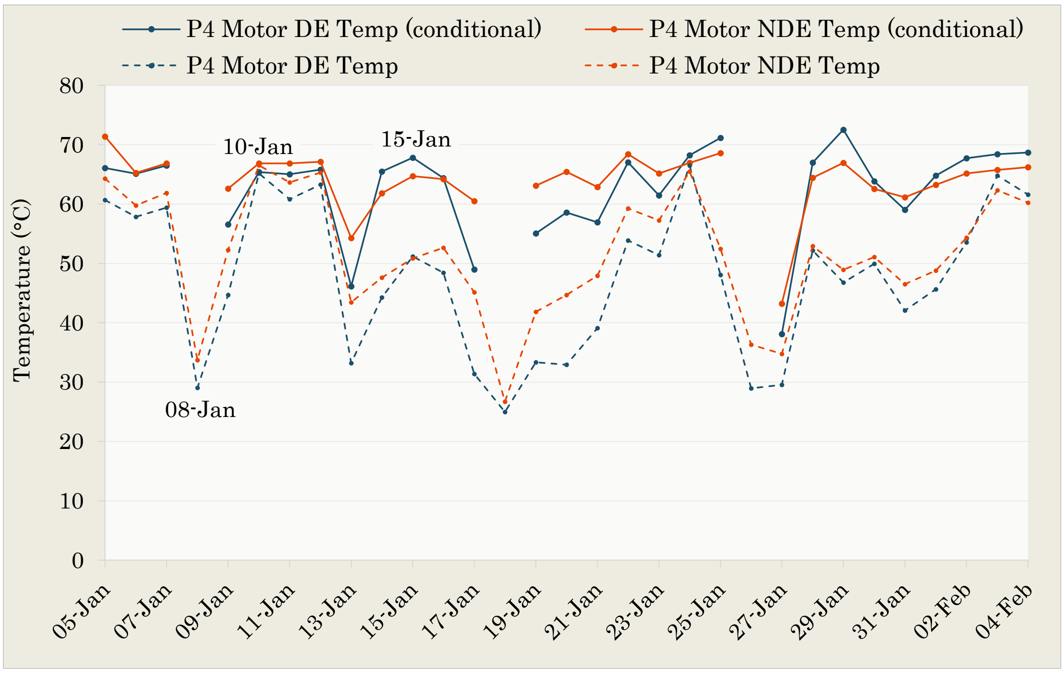


Figure 3.19: *30-day profile of daily temperature averages*

It can be seen that the conditional averages are generally higher than the averages that were calculated without a status condition. This is due to the fact that the non-operational temperatures (which are significantly lower than operational temperatures) are not used in the calculation. The following differences and similarities have been denoted on the graph:

- 08 Jan – The pump was not operational on this day, which resulted in the conditional average being omitted.
- 10 Jan – The pump was operational throughout the entire day, which resulted in equal averages on this day.
- 15 Jan – The pump was only operational for a limited duration on this day, which resulted in a considerable difference between the averages.

Log files can be compiled daily, hourly or every 30 minutes. Half-hourly log files consist of only a single time interval, meaning each log file will therefore contain only one value per parameter. Daily log files contain 48 values for parameters with a 30-minute interval configuration.

Figures 3.20 and 3.21 show screenshots of a half-hourly and a daily log file, respectively. The CSV file can be opened with a spreadsheet application such as Microsoft Excel[2] in order to filter the log file contents and view the incoming data. The half-hourly log file screenshot illustrates how 316 parameters have been filtered to only show the selected parameter's 10:00 average. Correspondingly, the daily log file screenshot illustrates how 15 168 entries have been filtered to only show the selected parameter's 48 averages.

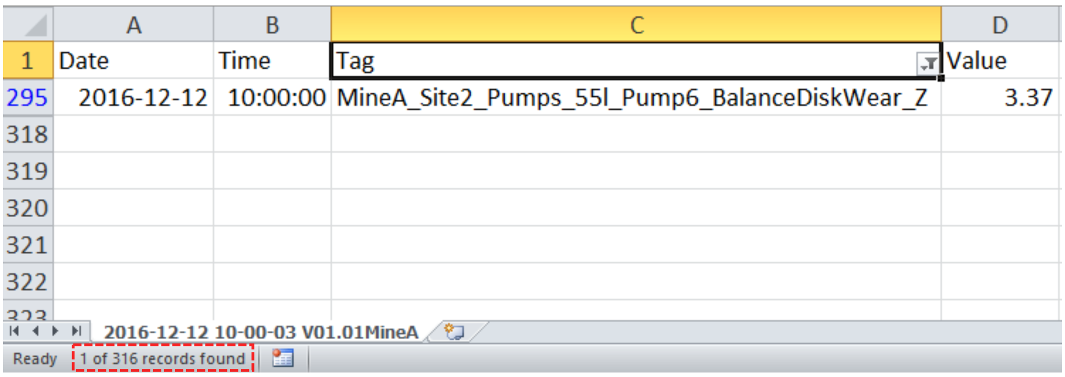


Figure 3.20: *Screenshot of a half-hourly log file*

[2]Microsoft Corporation – https://products.office.com/en-za/excel

	Date	Time	Tag	Value
245	2016-11-02	00:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.04
561	2016-11-02	01:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.11
877	2016-11-02	01:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.14
1193	2016-11-02	02:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.14
1509	2016-11-02	02:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.09
1825	2016-11-02	03:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.11
2141	2016-11-02	03:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.13
2457	2016-11-02	04:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.14
2773	2016-11-02	04:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.16
3089	2016-11-02	05:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.14
3405	2016-11-02	05:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.16
3721	2016-11-02	06:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	75.66
4037	2016-11-02	06:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	73.73
4353	2016-11-02	07:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	75.25
4669	2016-11-02	07:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	75.6
4985	2016-11-02	08:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	75.46
5301	2016-11-02	08:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	75.58
5617	2016-11-02	09:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	75.74
5933	2016-11-02	09:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	75.94
6249	2016-11-02	10:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.12
6565	2016-11-02	10:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.23
6881	2016-11-02	11:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.25
7197	2016-11-02	11:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.29
7513	2016-11-02	12:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	75.03
7829	2016-11-02	12:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	75.95
8145	2016-11-02	13:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	76.18
8461	2016-11-02	13:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	73.23
8777	2016-11-02	14:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	66.98
9093	2016-11-02	14:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	72.16
9409	2016-11-02	15:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	73.85
9725	2016-11-02	15:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	74.34
10041	2016-11-02	16:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	74.42
10357	2016-11-02	16:30:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	74.42
10673	2016-11-02	17:00:00	MineA_Site2_Pumps_55l_Pump5_Motor DE Bearing Temp_T	74.84

2016-11-03 00-00-01 V01.01MineA

Ready 48 of 15168 records found

Figure 3.21: *Screenshot of a daily log file*

The delivery of the log files and the reception thereof have a very high success rate. Emails from the remote servers are occasionally delayed due to the signal strength being precarious from time to time. Log files are kept in the spooler directory until the remote server's communication capabilities have been restored.

The processing of incoming log files was monitored and verified to be successful. Received values are written to the database and can be extracted to populate the report input sheets as required. Multiple reports were created and linked to different input tags, depending on the report type. Figure 3.22 is a screenshot of an *Exception report*'s input sheet, which was linked to 147 database tags.

	A	B
1	Tag ID:	90020
2	Tag Source:	9
3	Tag Unit:	mm/s
4	Tag Name:	MineA_Site2_Vent Fan 1_Fan NDE Vibration_V
5	Date:	2017-01-08
6	00_30	0.77
7	01_00	0.78
8	01_30	0.78
9	02_00	0.76
10	02_30	0.75
49	22_00	0.8
50	22_30	0.77
51	23_00	0.76
52	23_30	0.78
53	24_00	0.79
54		
55	Tag ID:	900208
56	Tag Source:	9
57	Tag Unit:	mm/s
58	Tag Name:	MineA_Site2_Vent Fan 1_Motor DE Vibration_V
59	Date:	2017-01-08
60	00_30	0.75
61	01_00	0.77
62	01_30	0.76
63	02_00	0.75
64	02_30	0.76
103	22_00	0.78
104	22_30	0.76
105	23_00	0.77
106	23_30	0.76
107	24_00	0.75

Site2_Input_Sheet

Ready 2350 of 7936 records found

Figure 3.22: *Screenshot of an input sheet for a daily report*

3.5 Summary

Mining sites have vast amounts of condition monitoring-related data that can be made available for analysis. Before it can be analysed, however, the required data needs to be collected, transferred, structured and stored. It would not be feasible to manually obtain and translate machine- and process data from one or more mining sites. A system was therefore developed to automate the data acquisition process.

Data from multiple mining sites can be centralised on a local server, located on the premises of a third party. Data preparation is, however, necessary in order to configure a system to automatically analyse the incoming data. Data preparation refers to the collection of data from remote servers, the pre-processing of measurements, the transfer of data from remote servers to a local database and, finally, the creation of the respective input sheets.

Available mining infrastructure was used to obtain measurements relating to the condition and performance of various types of equipment. A data logger was designed and developed to interface with a mine's SCADA system and create custom log files. The log files can be configured to contain 48 aggregated values, according to different operation types, e.g. average and maximum. Additional functionality was added to an existing data translation system, making it possible to translate the new data logger file format. The translation system was used to add the contents of log files to the database upon reception of new logs. Once added to the database, selected tag data can be extracted for a specified date range to create input sheets to be used in the analysis process.

CHAPTER 4

Operational condition assessment

4.1 Preamble

Evaluating the operational condition of mining machinery can be compared to a company performing a health assessment of its staff. The preferred approach would be to examine each staff member on a regular basis and analyse some key health indicators. This would result in early identification of any health risks and enable the company to schedule the relevant individuals for an appointment with the appropriate type of specialist. In most cases this may lead to the prevention of serious or permanent conditions.

Considering the use of diagnostic imaging in the field of medicine, highly specialised techniques such as magnetic resonance imaging (MRI) or computed tomography (CT) scans exist. It would, however, be too expensive and time-consuming to send all of the employees (most of them being healthy) for an MRI or CT scan each month. Correspondingly, a staff member who is having a heart attack, cannot wait for a month until his next appointment with a specialist. The staff member should also preferably see a cardiologist and not a radiologist, for example.

The most efficient strategy is therefore to make use of the proper specialist when it is considered to be necessary. It is, however, important to base this necessity on a number of health factors or indicators. A patient whose blood pressure is normal, is not necessarily healthy. The patient might have high cholesterol, which could lead to a heart attack. A patient with high blood pressure is also not necessarily suffering from a serious condition. In some cases, high blood pressure can be lowered by simply switching to a diet which contains less sodium.

This analogy aims to illustrate that the operational condition of mining equipment should be incorporated into the maintenance strategy. It is not feasible to manually inspect or conduct in-depth analyses on the mine's entire inventory of assets on a regular basis. A prognosis can therefore be very beneficial when planning and conducting a comprehensive analysis. In some cases only minor adjustments are necessary in order to prevent significant damage. Other cases require major repairs, which need to be planned in advance to minimise the effect of the maintenance intervention.

Maintenance costs can be reduced by investigating risk notifications and thereby prevent functional failures. High bearing temperatures could be the result of incorrect installation. Re-installing the bearings back into position would drastically improve a pump's operational condition, with minimal expenditure. Another possibility would be that the bearings (and perhaps other parts as well) are in fact worn and need replacement. The procurement of parts and scheduling of part replacements, before a breakdown occurs, will therefore minimise downtime and avoid a possible loss of production. In both cases, the use of CBM reduces repair and operational costs and increases the asset's effectiveness.

Many types of condition monitoring techniques exist. *Moubray* [79] discusses several types of monitoring categories and techniques for use in different types of applications. Some of these techniques are listed in Table 4.1. A common problem is, however, knowing when to perform which type of analysis. It is especially difficult on deep level mines due to limited access to the physical assets. Some are located on surface, while others are a few kilometres underground with some substantial distance between the equipment. Underground entry is also restricted during blasting shifts.

Table 4.1: *Condition monitoring techniques* (compiled from [79])

Particle	Chemical	Temperature	Electrical
Ferrography	Atomic emission spectroscopy	Infrared thermography	Power factor testing
Flow decay	Inductively coupled plasma	Focal plan arrays	Motor circuit analysis
Blot testing	X-Ray fluorescence spectroscopy	Fibre loop thermometry	Motor current signature analysis
Magnetic chip detection	Thin-layer activation	Temperature indicating paint	Power signature analysis
Sediment testing	Karl Fischer titration test		Magnetic flux analysis
LiDAR	Crackle test		Linear polarisation resistance

It is clear that various types of specialised analysis methods exist and could be instrumental in finding the root cause of operational deficiencies. The cost of the analysis can easily be justified if the analysis succeeded in identifying some type of irregularity. A first pass assessment, indicating where problems might exist, can therefore be a valuable input in the CBM process. Early detection followed by immediate corrective action is not only cost-effective, but will also contribute to the operational safety of the mine.

Several considerations need to be taken into account in order to successfully implement a CBM strategy on a deep level mine. *Dunn* [112], [113] is an experienced maintenance professional and writes about the trends and implications of condition monitoring. He lists several business needs that relate to the asset effectiveness of equipment. The information system and methodology that have been developed aim to fulfil three of those business needs, namely:

- The need for a holistic view of equipment condition;
- The need to reduce the cost of condition monitoring; and
- The need to optimise equipment performance.

4.2 Subsystem overview and requirements

Figure 4.1 shows the design elements that will be discussed in this chapter. These design elements relate to the methodology that has been developed. The first module explains how the four operating regions are used to assess the operational condition and performance of different types of equipment. The second module illustrates how the results, obtained from the analysis, are displayed graphically. The third module comprises a discussion on how these results are used to identify possible risks.

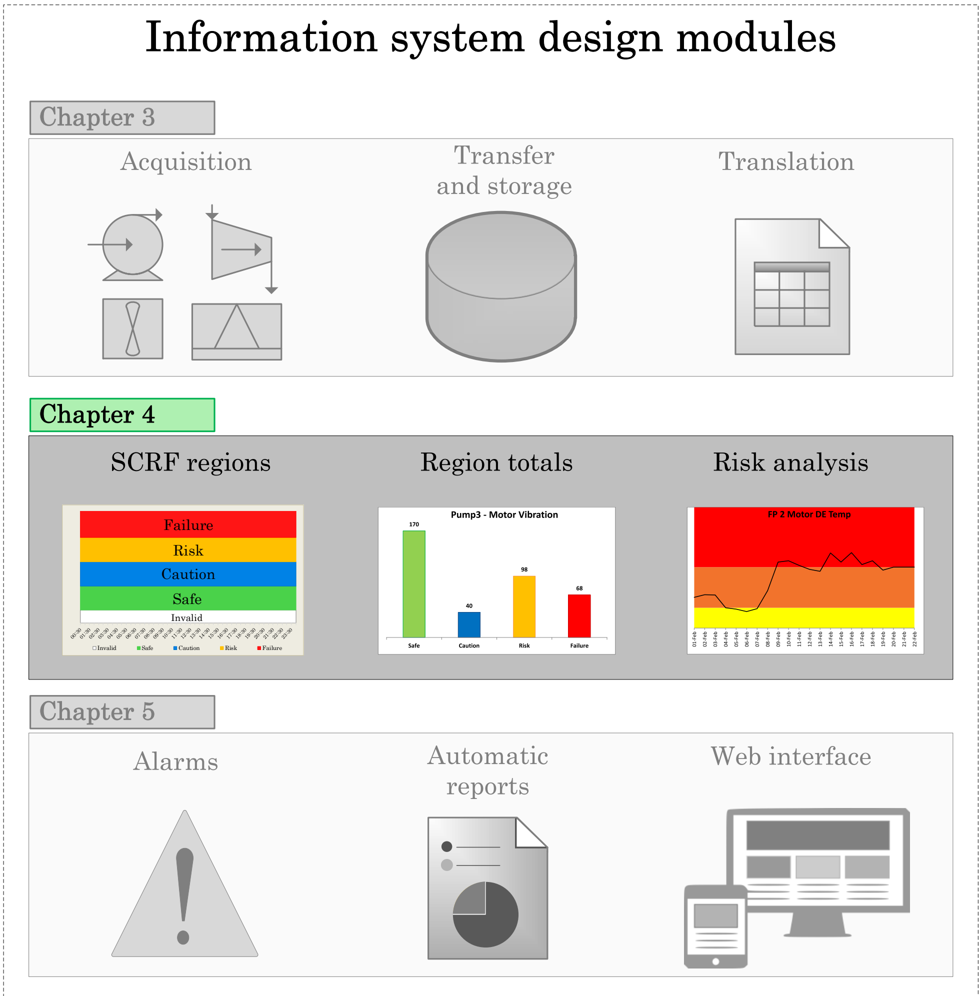


Figure 4.1: *Overview of Chapter 4 design elements*

An effective condition monitoring strategy can extend the operating life of equipment and increase the overall reliability of a system. Mining operations consist of several types of systems that need to be operational in order to maintain target production quantities. Many types of models and techniques are available to evaluate the temperature, mechanical wear, vibration and electrical parameters of industrial machines [114, 115]. These are all advanced analytical methods and cannot necessarily be implemented on a regular basis.

A methodology was therefore developed to automatically analyse various parameters for multiple types of systems on a daily basis. This can be seen as a first pass assessment which would indicate where symptoms of failure have started to develop. The information system can therefore provide a holistic view of equipment condition. A maintenance manager can use this information and assign the appropriate technician to investigate the failure symptoms. This would reduce the cost of condition monitoring by reducing unnecessary use of technicians and specialist instrumentation. Corrective maintenance can then eliminate these symptoms and restore the system to a preferred level of efficiency. In this way, operators and supervisors can optimise the performance of equipment.

The methodology compares the input data with four regions of operation: safe, caution, risk and failure (SCRF). Each region can be configured according to the relevant equipment's operating limits. A daily total for each of the four regions is calculated and stored for each parameter being analysed. These daily totals can then be compiled for a selected number of days, in order to determine whether any changes in the operational condition need to be investigated. A risk count can also be calculated to determine how often and to what extent a parameter is exceeding the safe operating limits.

Taking these considerations into account, the functional specification consists of the following:

- The SCRF region limits must be configurable for the user to choose component-specific limits.
- A daily total must be calculated for each parameter according to the relevant region limits.
- The region totals can be displayed for individual parameters, or added together and displayed as a component (or level) total.
- A daily risk count must be calculated for each parameter, according to its four region totals.
- 30-day profiles of the risk count and region totals must be compiled for parameters that have been identified as possible risks.
- A user must be able to evaluate multiple types of systems with the SCRF methodology.

4.3 Design detail and development

It has been established that a condition monitoring process is synonymous with data processing. Data can be obtained from various types of instrumentation and sensors. Input data needs to be analysed in order to identify unsafe or inefficient operation. Solutions that require the procurement and installation of monitoring equipment, which result in high capital expenditure, are currently not a feasible option for deep level mines that are under pressure to remain profitable. In the past five years the gold price has dropped by more than 20%[1], while the platinum price has dropped by more than 35%[2]. An innovative methodology was therefore developed to analyse multiple parameters across several types of systems. Parameters identified as risks are listed, and supplementary information regarding operational characteristics is provided.

SCRF regions

A CBM strategy necessitates that the operational condition of equipment is continuously monitored. An automated process is scalable, which makes it possible to easily expand the analysis. Whether 10 or 100 parameters are being analysed, the processing time will be practically the same. This, however, is not true for a manual process. A methodology, to be used in an automated process, was developed to identify operational risks. Maintenance personnel can then prioritise these risks and schedule inspections where necessary.

Four regions of operation are used to characterise the parameters selected for analysis. The four regions are labelled as safe, caution, risk and failure (see Figure 4.2). These regions can be configured for each individual parameter according to its operating limits. The failure region would typically range from the parameter's trip value to a percentage value below it. The remaining regions can be determined by using normal operating levels. Parameter-specific boundary levels (B_S, B_C, B_R and B_F) are therefore used to assess the relevant input signal.

A fifth region, namely the invalid region, is also used in the assessment. The purpose of the invalid region is to identify bad inputs. Measured values that are below a predefined maximum often goes unnoticed, because the system trips or warnings only compare the value with a high limit. This gives a false sense of safe operation and could potentially be dangerous. The accuracy (or correct installation) of instrumentation should therefore be verified when a parameter evaluation exhibits a high invalid count during periods of equipment operation.

[1]http://www.nasdaq.com/markets/gold.aspx?timeframe=5y
[2]http://www.nasdaq.com/markets/platinum.aspx?timeframe=5y

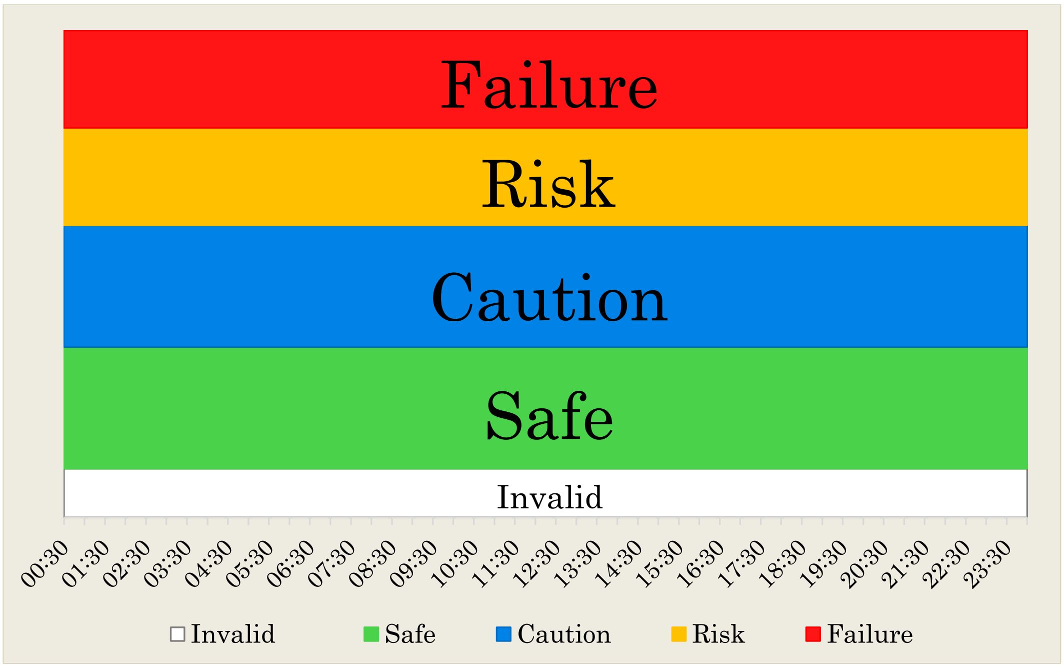


Figure 4.2: *Design of SCRF regions*

Figure 4.3 illustrates how the analysis is performed. Each of the 48 vibration values is compared with the respective boundary limits. The four region totals (T_S, T_C, T_R and T_F) represent the number of data points that lie within the relevant region. The region totals for this example can be seen in Figure 4.4 (B). The same procedure can be followed for the remaining pump parameters. Parameter totals can then be added together to obtain a holistic pump analysis.

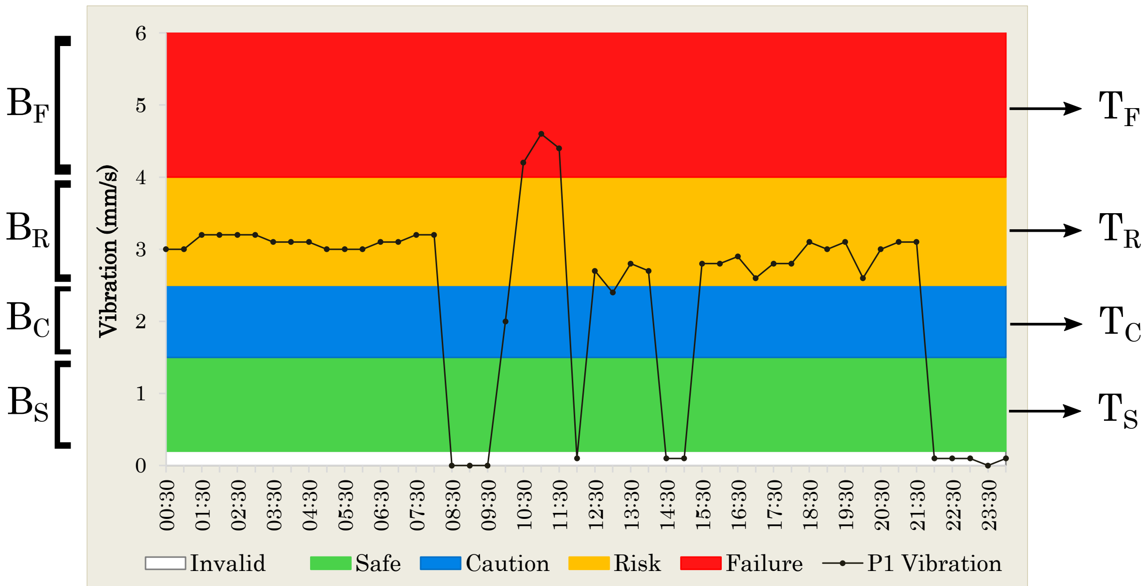
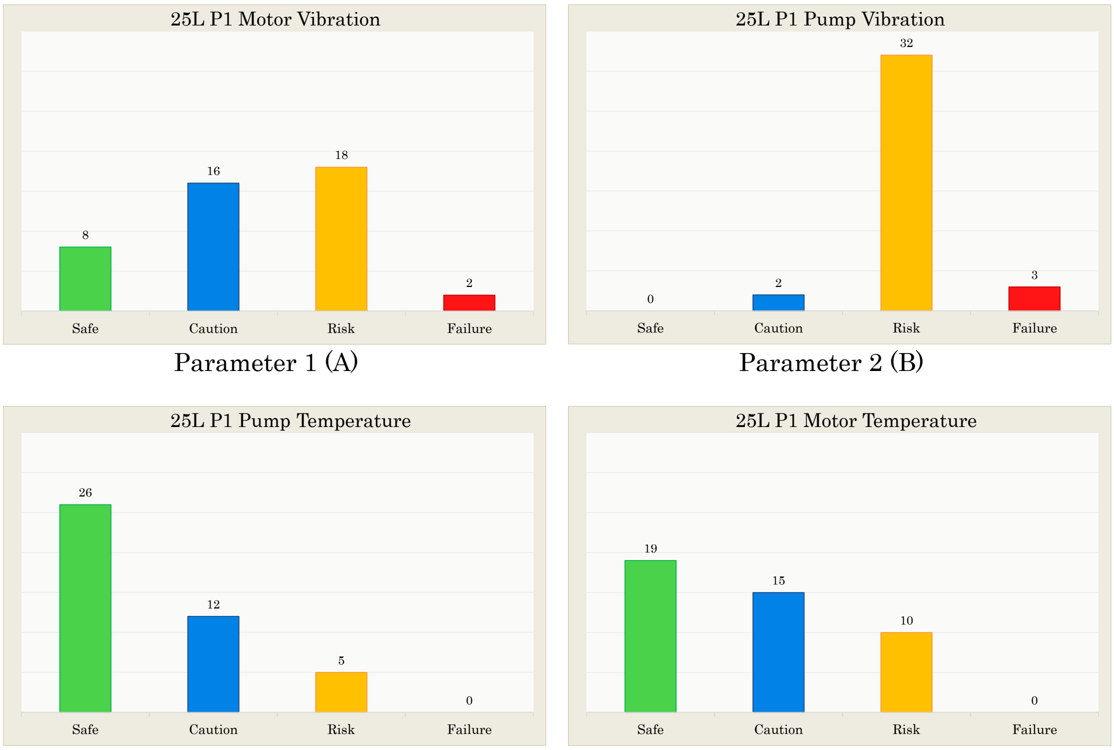


Figure 4.3: *Example of SCRF analysis*

Region totals

As mentioned before, several pump-, compressor-, fan- or fridge plant parameters can be included in the analysis. The following example demonstrates the analysis process of four pumps, each consisting of four parameters. Figure 4.4 shows the daily totals of these selected parameters. This type of graphic display makes it easy to identify parameters that are exceeding their safe region limits.



Parameter 1 (A) Parameter 2 (B)

Parameter 3 (C) Parameter 4 (D)

Figure 4.4: *Individual parameter totals*

These individual parameter totals can be combined to produce a single result per component. This enables maintenance personnel to determine where attention is needed, without having to examine all the parameters of every component. Figure 4.5 shows the combined totals of the four example parameters. This procedure can be followed for all the pumps in the water reticulation system. A level-specific analysis can therefore be performed by grouping corresponding pump evaluations together.

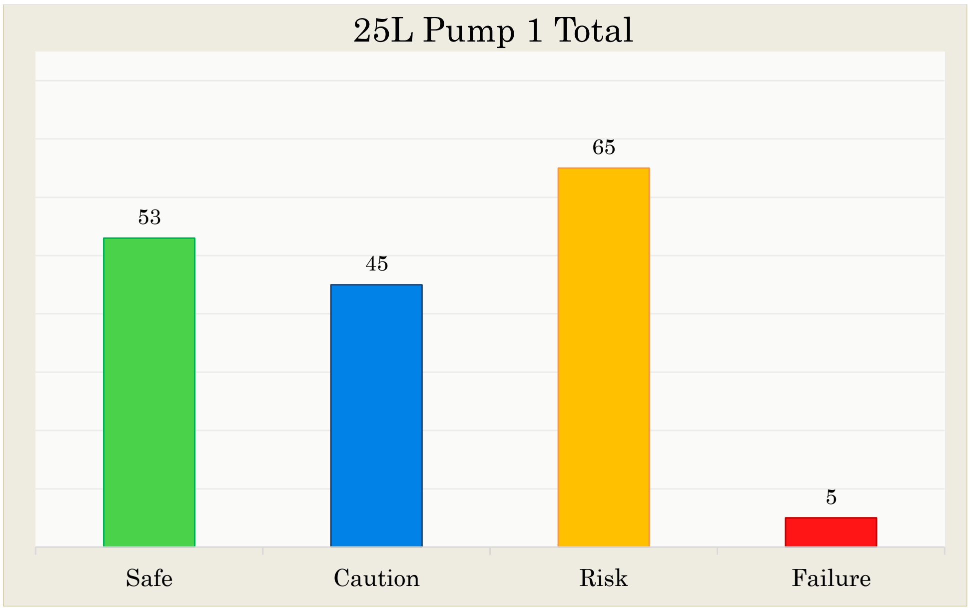


Figure 4.5: *Pump parameter totals combined*

The results from a system- or level analysis can be summarised by displaying the risk and failure region totals of the respective components. This gives the user an overview of the components' operating regions. Figure 4.6 shows the risk- and failure region totals of the four example pumps. It is clear that *Pump 1* and *Pump 4* are exhibiting symptoms of operational risks, which need further investigation.

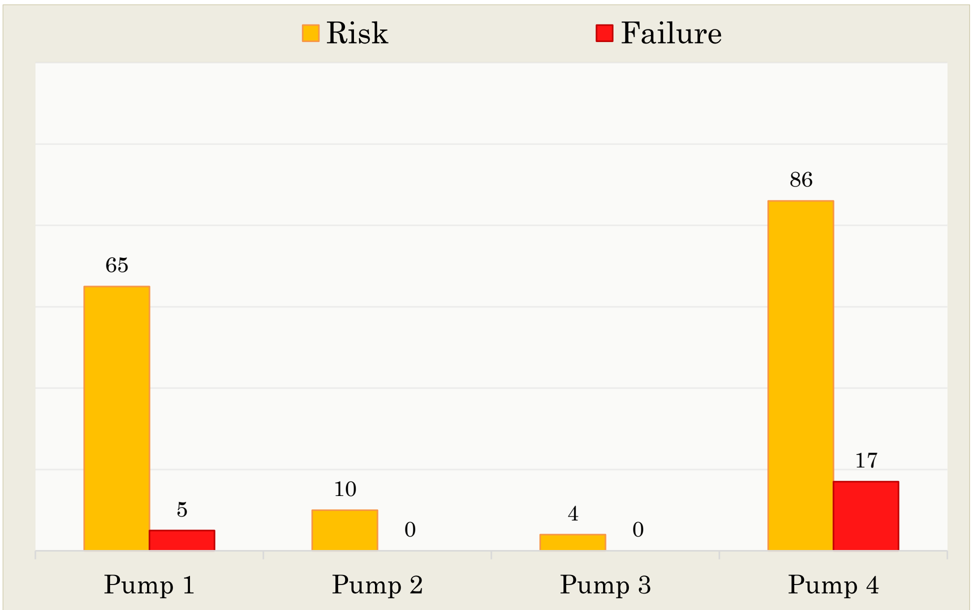


Figure 4.6: *Risk- and failure region totals for level analysis*

It is important that the summarised information is supplemented with some detail regarding the specific parameters that were identified as possible risks. Figure 4.7 shows each parameter's contribution to the failure region totals of *Pump 1* and *Pump 4*.

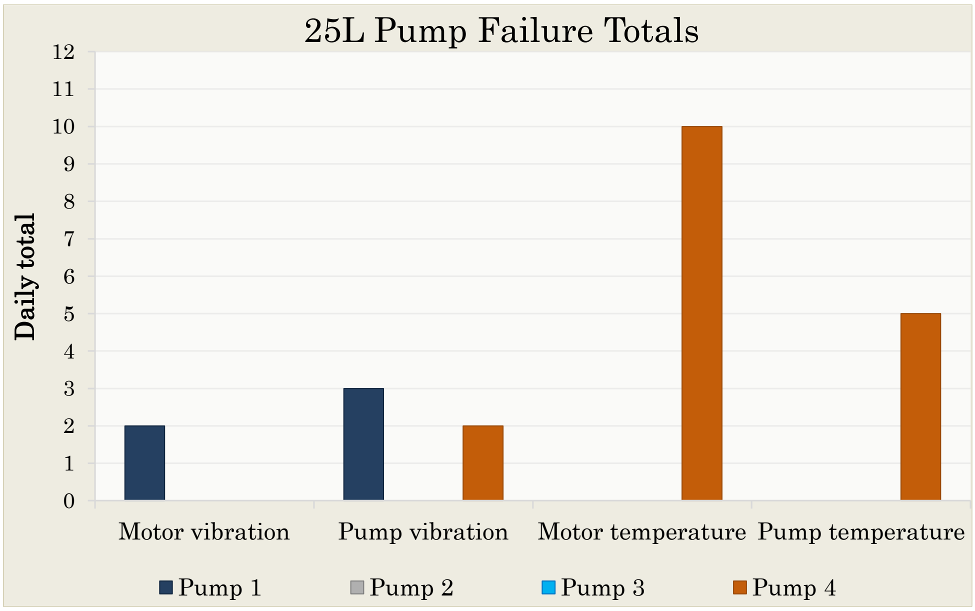


Figure 4.7: *Parameter failure region totals*

It is also important to indicate which parameters are operating within their respective risk regions. Although these parameters might not need immediate attention, it would be advised to monitor them. The risk breakdown for the four example pumps can be seen in Figure 4.8.

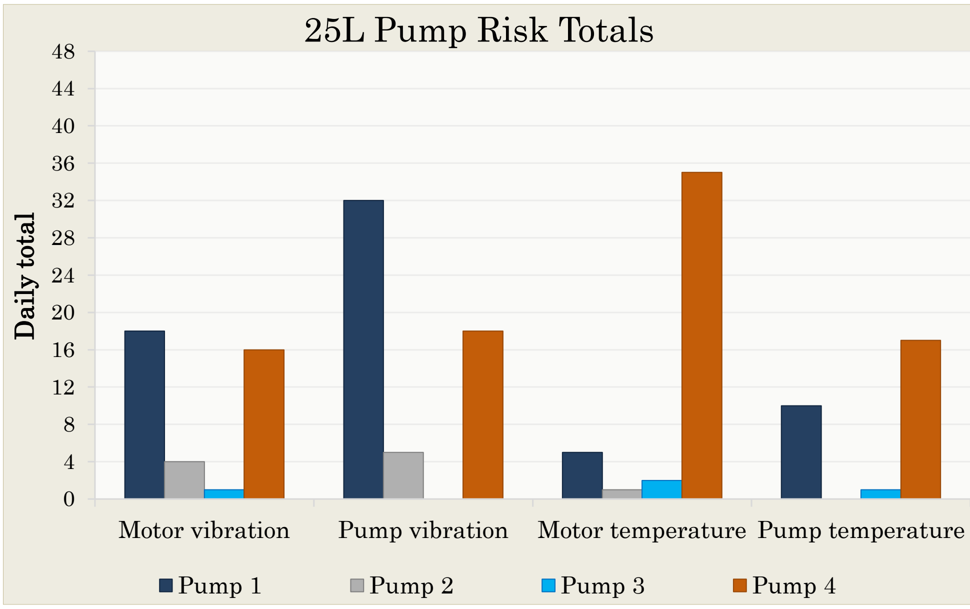


Figure 4.8: *Parameter risk region totals*

Risk analysis

The final step in the analysis process is to determine where attention is needed. The aim is to minimise the time it takes for the user to interpret the analysis results. This can be accomplished by firstly compiling a 30-day profile of the four region totals for each parameter. Figure 4.9 illustrates such a profile for a selected parameter. The region totals shown in Figure 4.4 (C) are the daily totals of 12 February, as indicated on the profile plot.

From the profile plot it is clear that the parameter is exhibiting signs of deterioration. During the first week, the bulk of the operation took place within the safe region. The safe region operation then started to decline and an increase in the caution and risk regions can be observed. The risk region operation continued to increase, and during the last week a large portion of temperature measurements were in the failure region.

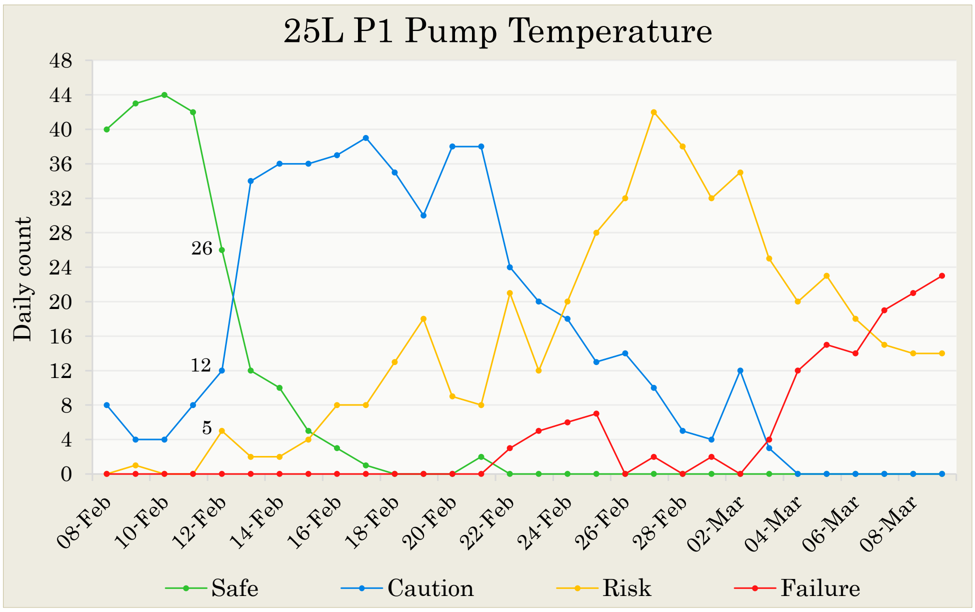


Figure 4.9: *Example of a 30-day region total profile*

Each parameter's daily totals are subsequently translated into a risk score. The risk score is calculated by means of a weighted sum of the caution-, risk- and failure region counts. The running hours percentage is used to adjust the risk score, to account for equipment that was only operational for a short while.

The risk scores are divided into three risk categories: low-risk, medium-risk and high-risk. Medium- and high-risk parameters are included in the condition monitoring report. This enables the user to evaluate the risk parameters, over a period of 30 days, with ease.

Figure 4.10 shows the corresponding risk score profile for the pump temperature evaluation shown in Figure 4.9. The risk score profile indicates that a negative (upward) trend started to develop and continued to do so due to lack of maintenance. A CBM strategy can therefore be configured to generate a service request when a parameter's risk score continues to increase for a selected number of days.

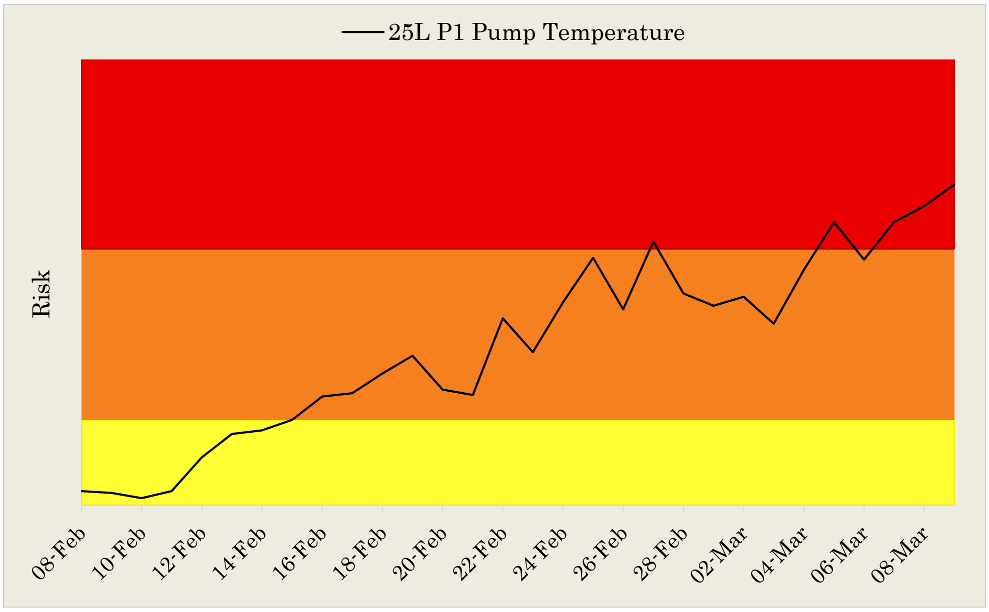


Figure 4.10: *Example of a 30-day risk score profile*

The results from the risk analyses, together with the four region total profiles, make it possible to identify and evaluate possible operational risks. Instead of having to monitor several systems, each with many parameters, maintenance personnel can focus on these risk notifications.

4.4 Module verification

The system functionality was verified to comply with the requirements and detailed specification. This was done by performing several types of verification tests. The first step of the verification process was to compare the results from the automated procedure with an alternative calculation method. Region limits were therefore specified (Figure 4.11 [A]) and a simulated input signal was compiled (Figure 4.11 [B]). The results from the automated system (Figure 4.11 [C]) were compared with values obtained from a *Count if* function (Figure 4.11 [D]). Both of these two methods produced an equal number of occurrences for each of the respective input values. The region total calculation was therefore successfully verified.

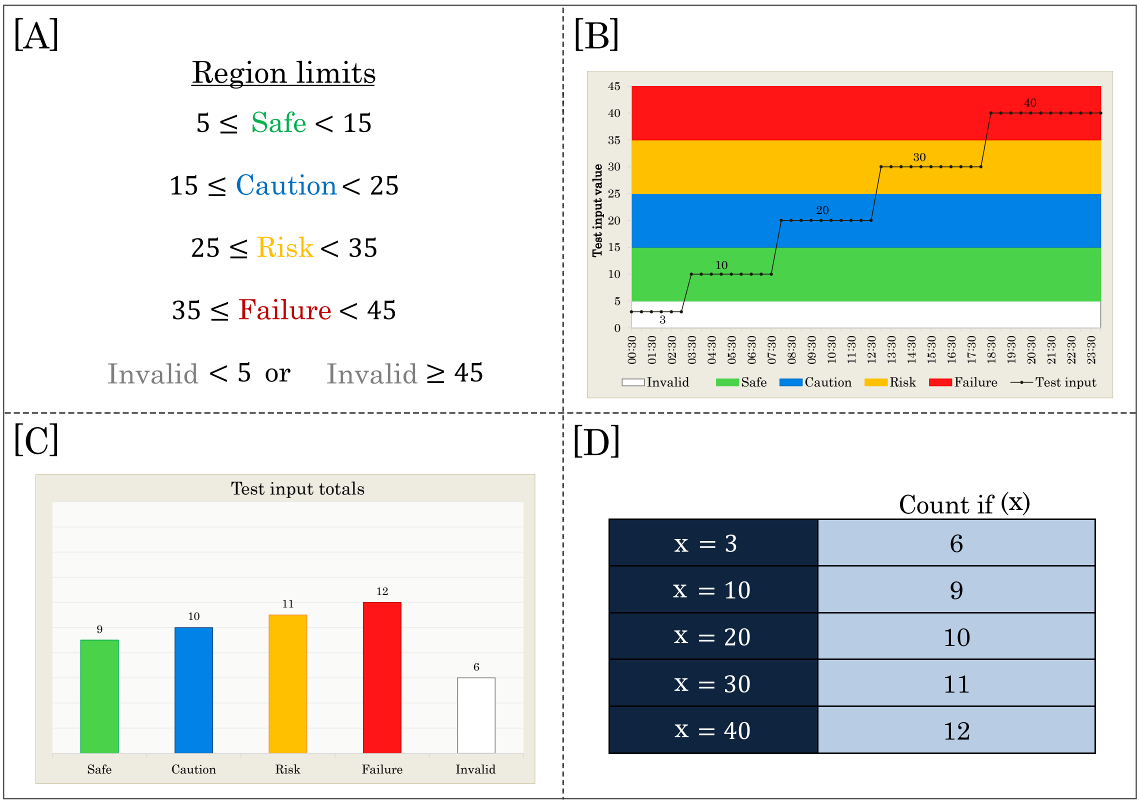


Figure 4.11: *Verification of region total calculation*

According to the functional specification, the information system is required to evaluate multiple types of mining systems. Data from four mining systems were used to verify the multiple system type functionality. Several parameters from each of the four systems were analysed according to their respective operating limits. Figure 4.12 shows an example input parameter for each system.

SCRF region limits (indicated on each graph) were determined for the various parameters. The SCRF region totals were calculated and can be seen in Figure 4.13. These region totals show that various types of systems, as well as different types of parameter inputs, can be analysed and compared. Once the region totals have been determined, they can be added to a 30-day profile graph or be used to calculate a risk count, regardless of the system type. It was therefore verified that a user can configure parameter-specific region limits and that multiple types of mining systems can be analysed.

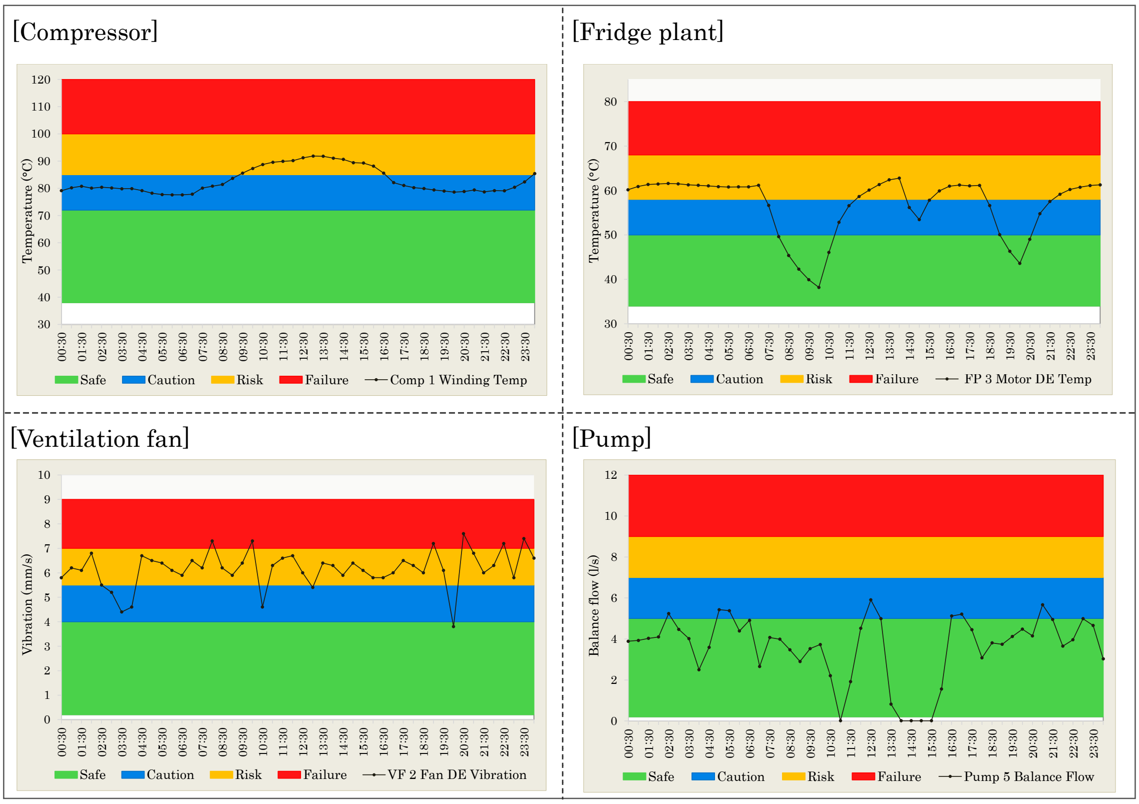


Figure 4.12: *Multiple system input verification*

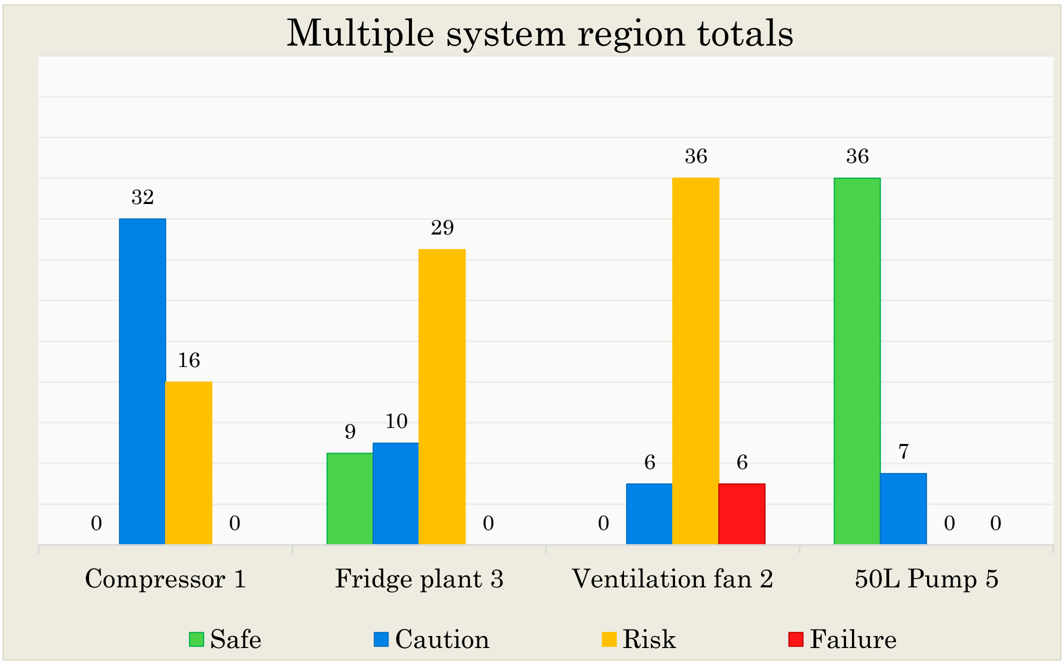


Figure 4.13: *Multiple system region totals verification*

Another verification test was performed to verify that the methodology produces an accurate representation of the equipment's operational condition. A parameter, primarily operating in the failure region, was identified and analysed. Figure 4.14 shows a daily profile of the selected motor bearing temperature. The maximum allowable temperature (PLC trip limit) of the relevant motor bearing was set at 72°C.

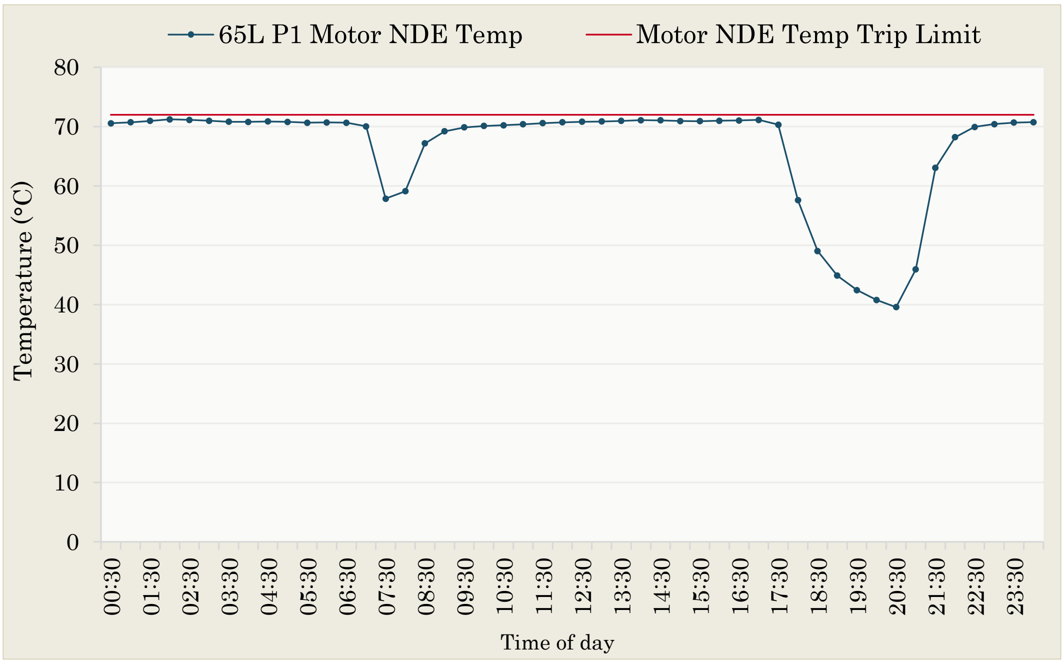


Figure 4.14: *Pump 1 bearing temperature profile*

Historical data was obtained to analyse the bearing temperature. The SCRF analysis was performed on 10 weeks' data. The results from the analysis indicated that the temperature progressed from the low risk- to the high-risk category. Figure 4.15 shows the region totals of the 30-day period during which the risk score started to increase. The corresponding risk profile is shown in Figure 4.16.

These profiles suggest that the bearing temperature increased over time and remained high. During the first two weeks of the 30-day period, elevated risk region totals can be observed. The main operating region subsequently moves from the risk region to the failure region. This indicates that the motor is constantly operating close to the specified maximum temperature. A statistical analysis was therefore performed to verify these findings.

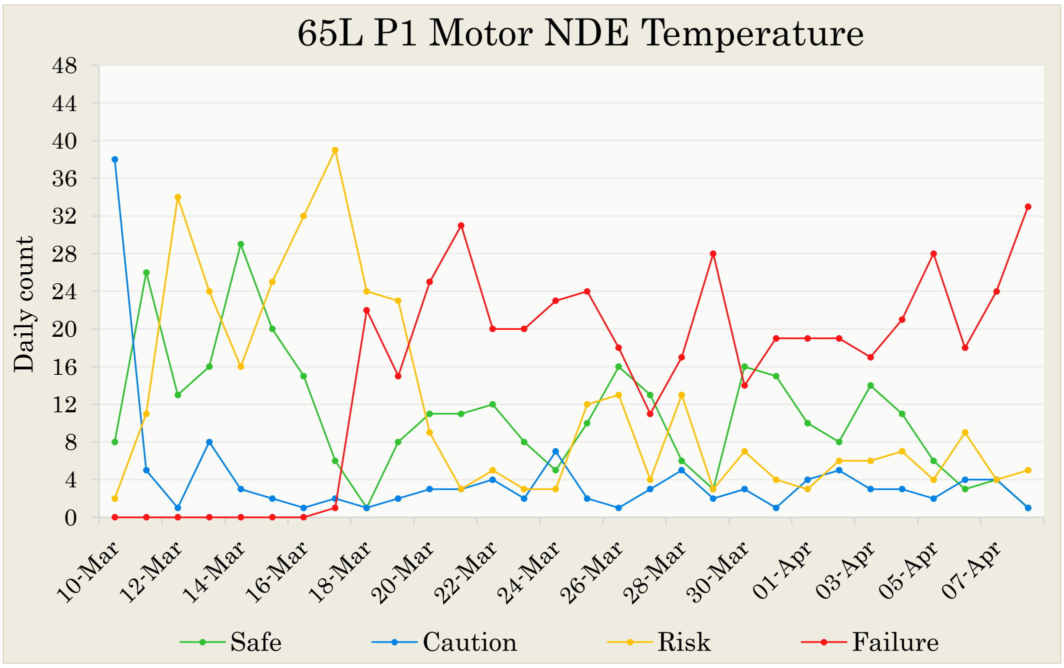


Figure 4.15: *SCRF profile – Pump 1 bearing temperature*

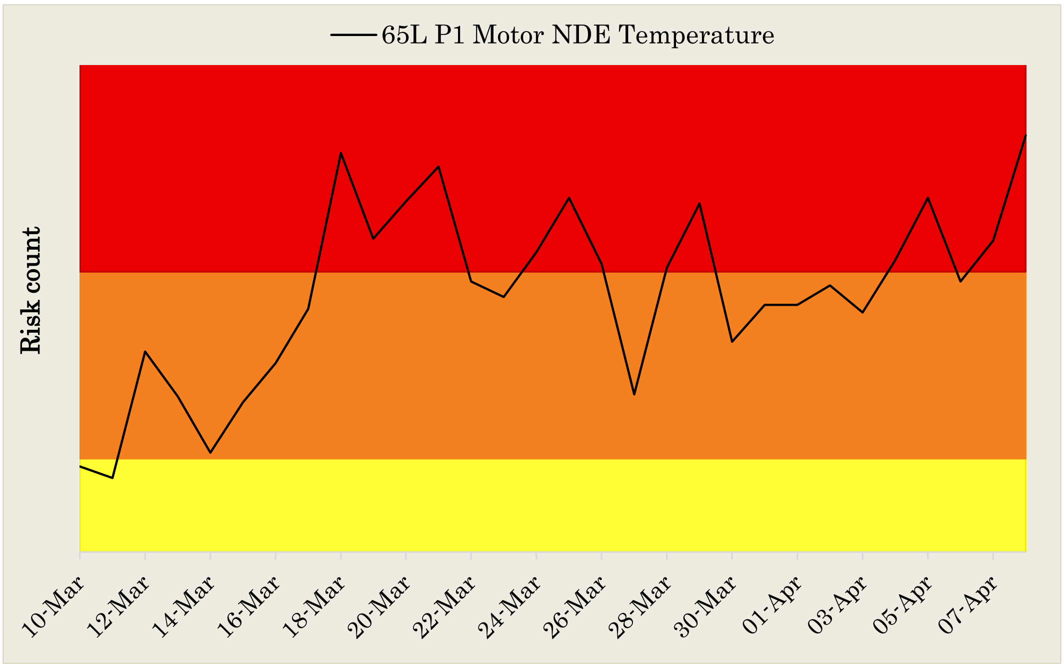


Figure 4.16: *Risk score profile – Pump 1 bearing temperature*

A distribution plot was constructed for each of the 10 weeks. These plots can be seen in Figure 4.17 and illustrate how the average and maximum temperature gradually increased. ΔT_1, which represents the difference between the average of Week 1 and the average of Week 10, was measured to be 1.3°C. ΔT_2, which represents the difference between the maximum of Week 1 and the maximum of Week 10, was measured to be 4°C.

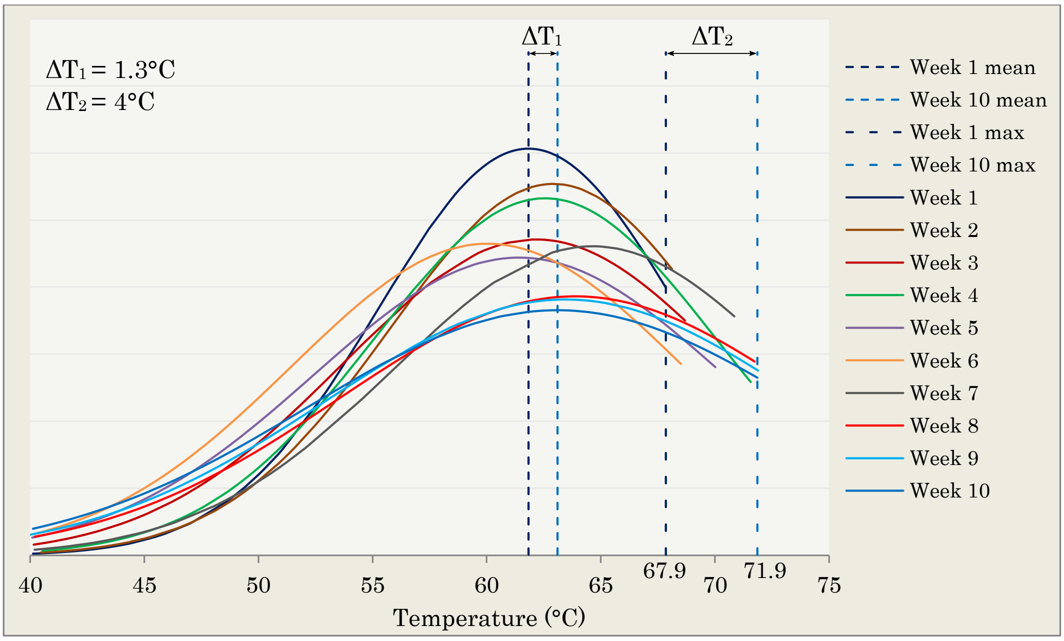


Figure 4.17: *Temperature distribution plot*

The statistical analysis has shown that the temperature measurements deteriorated from an acceptable range to a range where the values are approaching the maximum allowable temperature. It was therefore verified that the methodology provided an accurate evaluation of the temperature measurements. A holistic assessment of the equipment's operation can thus be obtained by using the same method to assess multiple parameters before consolidating the results.

4.5 Summary

The implementation of a CBM strategy can result in high capital and operational expenditures, especially on deep level mines where multiple types of systems and machinery are in operation. Condition monitoring systems, consisting of different types of instrumentation, are expensive to purchase, install and configure. An information system, capable of monitoring multiple types of mining systems, was therefore designed to make use of existing infrastructure and evaluate the available data.

An innovative methodology was developed to assess different types of input signals and present the results in a graphical format, which makes it easy to interpret. Four regions of operation are used to determine whether installed equipment (i.e. pumps, compressors, fridge plants, or fans) are exhibiting signs of unsafe or unsound operation. These regions can be configured to be component-specific, ensuring that the appropriate operational limits (which vary for different makes and models of machinery) are used. The analysis is performed on a daily basis on multiple parameters per machine. This enables maintenance personnel to identify specific areas that need attention.

The analysis approach described in this chapter was specifically designed and developed for deep level mines. Deep mines differ greatly from manufacturing plants where equipment is, in general, well instrumented, easily accessible and operated in a controlled environment. Mining machinery is constantly subjected to extreme environmental and operational conditions. This necessitates a regular system evaluation to prevent failure symptoms from developing into a serious condition where a functional failure is imminent.

Regular system evaluations by means of manual inspections are, however, not feasible due to the size and limited accessibility of a mining operation. A first pass assessment, indicating where an in-depth analysis is needed, can therefore be a valuable input when making maintenance decisions. It can subsequently be concluded that the information system provides a user-friendly, cost-effective, CBM solution to what would otherwise be a time-consuming and expensive undertaking.

CHAPTER 5

Information and exception reporting

5.1 Preamble

The manner in which the results from a system analysis is presented has a significant impact on the underlying benefit that can be derived from the analysis. Information needs to be structured, filtered and displayed in such a way that the relevant stakeholder can easily view and interpret the analysis outcomes. Important alerts or exceptions can go unnoticed if a report contains superfluous information. Different types of communication media were therefore used to effectively convey vital notifications.

Figure 5.1 illustrates how the data from multiple mining systems are converted from raw data into information. Subsystem limits are determined for each parameter being analysed. These limits are used to configure alarms on the EMS server. Alarm messages can be sent directly to personnel when a parameter value exceeds the high set point limit.

A system analysis is also performed for each of the respective systems, using the four region limits (see Chapter 4). Formatting values are subsequently assigned to each subsystem, according to the calculated risk scores. The formatting values are used to colour code the system layout on the web interface to indicate where exceptions exist.

The results from each of the respective system analyses are compiled in a system-specific report. Exceptions from all the systems are summarised in an additional report. The exception report provides a high-level view of the operational risks. Reports are generated daily and each report can be sent to selected recipients.

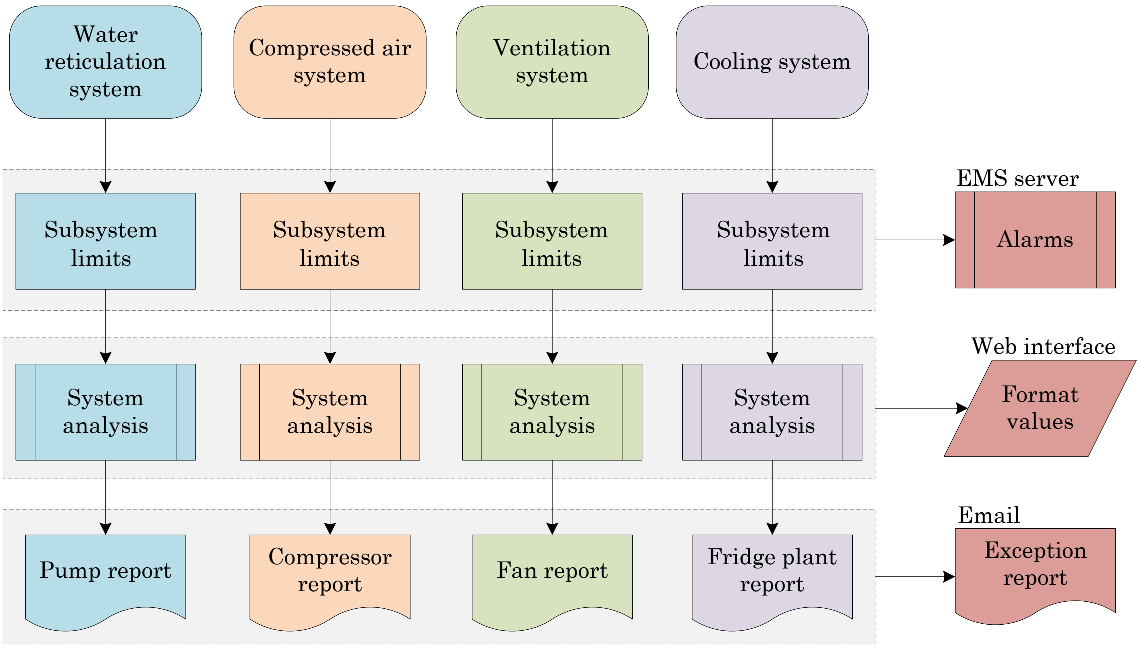


Figure 5.1: *Functional diagram of the information reporting process*

The information system addresses several of the *operational awareness needs* that are experienced on deep mines. Vast amounts of data are generated daily and stored on data historians. Although the data is accessible, it is not readily available. It is also not practical to examine the unprocessed and unstructured raw data in order to determine where attention is needed. Information is therefore supplied to the relevant team members in different formats:

- On-site alarms compare real-time data to preset limits and can therefore alert personnel immediately if the limits are exceeded.
- Automated system reports are sent out daily and contain analysis information from the previous 30 days (or other desired time period).
- The detailed system-specific reports can be sent to the respective foremen and the summarised exception report can be sent to the senior engineers.
- An online platform provides a holistic view of the mining operation, with colour formatting being used to show where operational risks have been identified.
- Historical data, as well as *live* half-hourly data can be viewed on the online platform.

Mine personnel are therefore continuously made aware of system inadequacies and risks. The simplified risk identification approach enables managers and supervisors to determine where attention is needed most. The evaluation of several parameters per subsystem makes it possible to generate service requests more effectively. A maintenance technician can inspect the list of service item requests during a single call-out. Replacement parts can also be ordered in advance where necessary.

The availability of both information (risks and exceptions) and system data (raw parameter values) is vital to maintain the systems and equipment on a mine. Multiple users can be given access to the online platform, which can be accessed irrespective of the time of day or their location. Website sign-in only requires internet access, which means users do not have to be on site where they are connected to a local network. Data from all the configured systems are updated every 30 minutes on the web interface. The formatted layout directs the user to the problem areas within each major system. This significantly reduces the time and effort it takes to monitor parameter values that require further consideration.

The aim is to continuously analyse a large number of parameters, identify operational risks and provide summarised feedback. The information system automatically collects data, performs various system evaluations and sends reports and notifications to relevant personnel. The reports and online platform were designed to be included in the maintenance strategy of a mine. Maintenance requests can thus be generated prior to equipment breakdown or system stoppage.

5.2 Subsystem overview and requirements

Figure 5.2 shows the design elements that will be discussed in this chapter. These design elements are used to facilitate the notifications and alerts regarding the risks that were identified by the operational condition assessment. The first module demonstrates how real-time notifications are sent by configuring alarms on remote servers located on site. The second module discusses the design and customisation of the automated reports. The third module explains the functionality of the online platform and the features thereof.

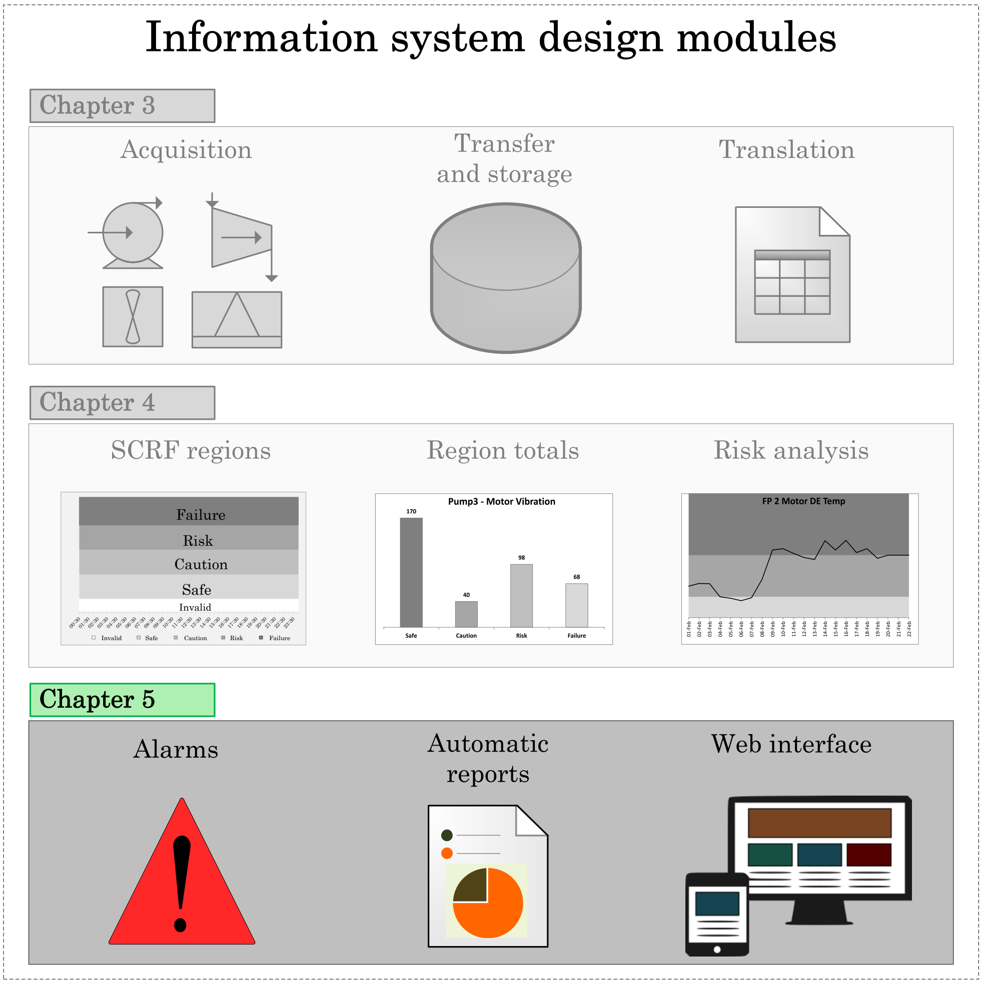


Figure 5.2: *Overview of Chapter 5 design elements*

Centralised information is in high demand on deep level mines, due to the size and diverse nature of these mining operations. The information system was therefore developed to structure machine- and process data of multiple mining systems, simplify analysis results and make the information accessible to all the parties involved. This eliminates the need to request, or manually download, system data for a specified time interval. The daily reports, used in conjunction with the online platform, can be used to investigate alarm alerts and monitor parameters identified to be at-risk.

Alarms can be configured for selected parameters (e.g. gearbox vibration) per subsystem (e.g. Compressor 1). Component-specific limits can be used when configuring alarms. The allowable violation duration (the time period that a parameter can exceed the specified limit before triggering the alarm) can also be set for each alarm. Alarm notifications can be sent to a list of recipients and each recipient can receive the notification via email or SMS.

The automated reports contain medium- to long-term analyses and aim to identify developing trends that require further investigation. Each report contains a calculation script which executes a list of functions and procedures. Although many parameters are evaluated in each report, only some (based on their risk score) are added to the report sheet.

Users can access system data, obtained from half-hourly log files, and analysis information via the web interface. A user can navigate to a specific parameter profile by selecting the mine group, mining site, system and subsystem. Daily health status values are calculated for each system and subsystem. Health statuses are divided into three categories, namely good, warning and critical. The online colour markers are a representation of the health status and the markers are formatted according to the status values.

Taking these considerations into account, the functional specification comprises the following:

- The user must be given the option to configure alarms according to component-specific parameter limits.
- The user must be able to configure the allowable violation duration for each alarm.
- Each report must be generated automatically according to an interval selected by the user.
- The content, layout and recipient list must be customisable for each report.
- The online platform must make historical data available for all the systems and subsystems.
- *Live* data for the current day must be updated online every 30 minutes.
- Operational health indicators must be used to visualise the risk information.
- Health status values for all the systems and subsystems must be calculated and updated online on a daily basis.

5.3 Design detail and development

The information reporting module was designed to simplify the monitoring and identification process of at-risk mining systems. Alarms provide real-time violation notifications, while weekly and monthly analyses provide a longer-term risk evaluation. Results from the analysis scripts are compiled in reports that are generated and sent out automatically. Automation was necessary to analyse the large number of data sets on a regular basis. The values that are displayed on the web interface are linked to database tags that are also updated automatically, upon completion of the calculation scripts.

Alarms

Trip limits on mining equipment are generally configured as a safety precaution. Equipment will therefore be auto-stopped when a parameter value exceeds the trip-limit set point. Senior engineers who are responsible for the equipment, and the maintenance thereof, are not always made aware of trips. Constant tripping necessitates a service investigation and failing to do so may shorten the operational lifetime of equipment. It was therefore decided that notifications should be sent to selected personnel when parameters are approaching their respective trip limits. This enables supervisors to keep track of when and how often the measurements exceed their safe operating limits.

Alarms were configured with an existing alarm manager application on the EMS servers on site. Alarm tags were created to compare the input value with the relevant limits. In some cases an additional condition was needed to determine whether a start-up event is in progress. Vibration values, for instance, tend to increase significantly for short periods of time during a start-up procedure. Two separate limit set points (a low limit and a high limit) were therefore combined with a start-up condition to prevent false alarms.

An alarm will be triggered if the alarm tag value is equal to one (1) for a specified time period. The alarm tag is programmed to compare the input value with the low limit during normal operation. If the input exceeds the low limit set point, the alarm tag's output will be one (1). The alarm tag's output will, however, remain zero (0) if the input exceeds the low limit during a start-up event. A high-limit set point is used in conjunction with the low limit, as a safety measure. When a value exceeds the high limit, the alarm tag's output will be equal to one (1), irrespective of a start-up procedure.

Figure 5.3 illustrates the methodology which is used to configure the alarms. The allowable violation duration in the diagram is five minutes. This is only an example value and can be set by the user. Once an alarm is triggered, an alarm message will be sent to the list of recipients via email or SMS.

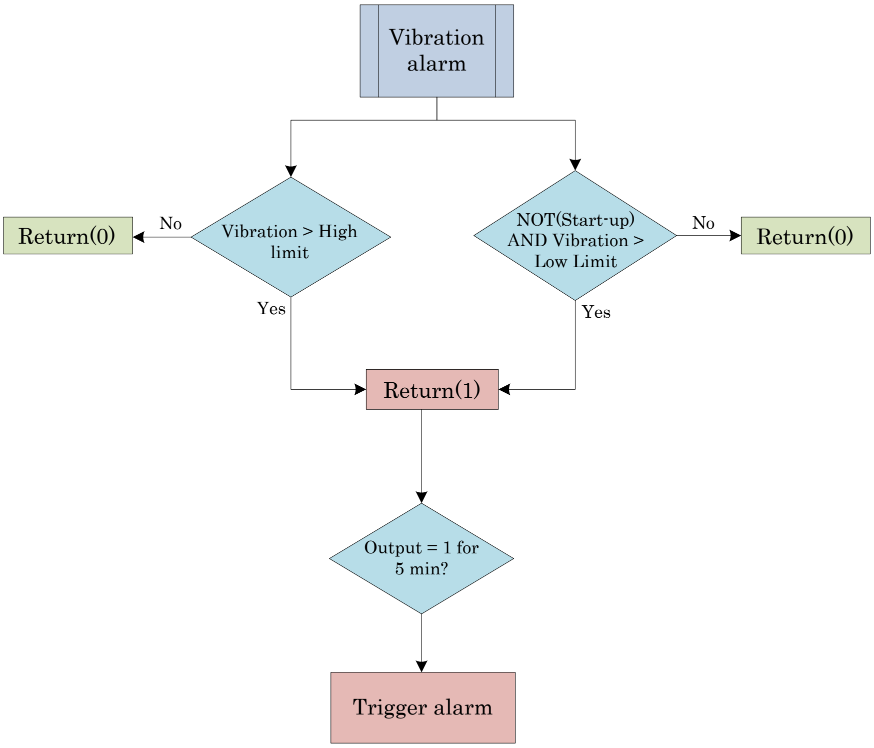


Figure 5.3: *Alarm procedure methodology*

A *running status* tag returns a value of one (1) when the relevant machine is operational and returns a value of zero (0) when it is not operational. A *change* tag returns a value of one (1) when the input tag value changes. The change tag value will reset after T_r minutes (set by user) and return a value of zero (0). A change tag value of one (1) therefore represents a start-up or shut-down occurrence.

In the event of running status tags being unavailable, a start-up procedure can be detected by using a *change* tag and a *programmable* tag. The *programmable* tag was used to compare the input tag value with a threshold value. The tag was therefore configured to return a value of one (1) when the power tag value is above a selected threshold and returns a value of zero (0) when the power tag value is below the threshold:

If power > threshold:
return (1);
else return (0);

Figure 5.4 illustrates how a start-up procedure is detected by using a power tag and a *programmable* tag. The *programmable* tag changed from zero (0) to one (1) when the power measurement exceeded 600 kW. This resulted in the *change* tag value being set to one (1) for a period of 10 minutes (T_r).

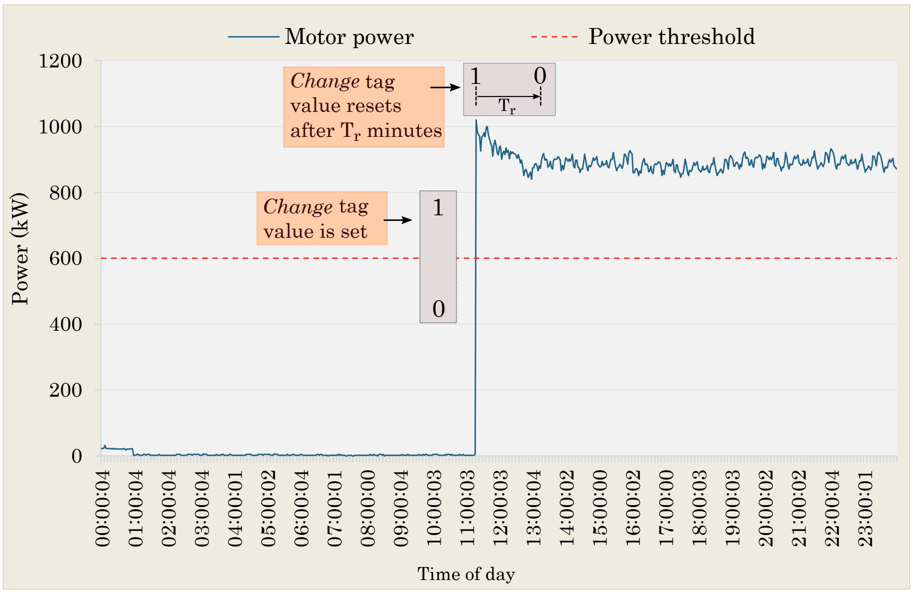


Figure 5.4: *Start-up procedure detection*

Figure 5.5 shows an example of a motor vibration alarm event. A low limit and a high limit were set at 2 mm/s and 4 mm/s respectively. Excerpt A (shown in figure) demonstrates how the *change* tag value is set and reset.

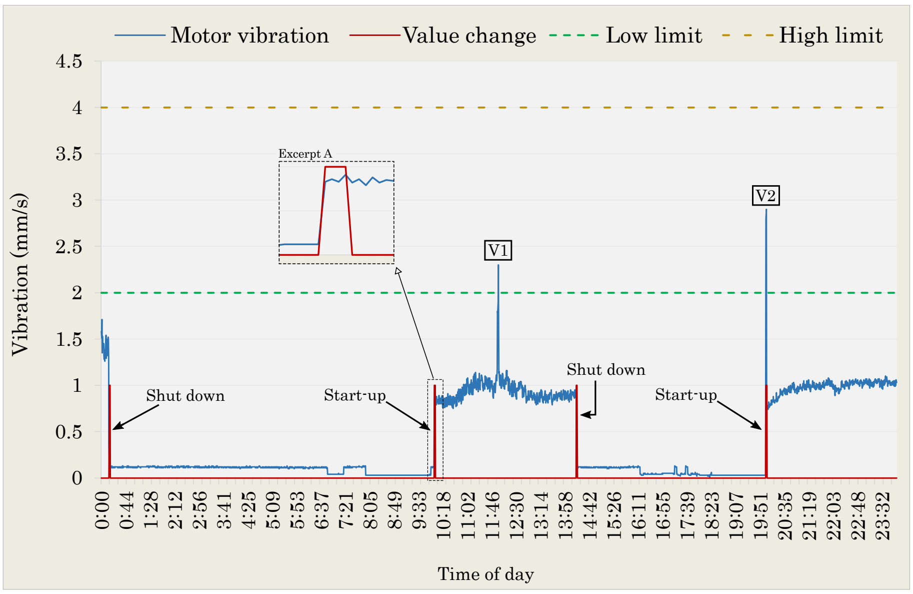


Figure 5.5: *Example of motor vibration alarm*

The motor vibration exceeded the low limit on two occasions. The first violation (V1) occurred during a period of normal operation. This occurrence therefore led to a value of one (1) being returned by the alarm tag. The second violation (V2) occurred during a start-up event. The alarm tag value therefore remained zero (0). Alarm notifications are sent when the alarm tag value is equal to one (1) for a time period that exceeds the allowable violation duration. Notifications can be sent to a list of recipients via email or SMS.

Automatic reports

The main objective of the data analysis is to identify failure symptoms or possible risks. This information can be used to prevent system failures and equipment damage. It is therefore vital to only include the necessary results when compiling reports. The report structure and content should be simplified and easy to interpret.

An existing translation system was used to generate the automated reports. This system was designed to translate energy data and generate energy-related reports. Reports are generated by creating an input sheet with the required data and executing a calculation script. The final report is sent to the recipient list via email. Reports can be generated daily, weekly, monthly, or yearly.

Two types of reports were designed and developed to provide relevant stakeholders with necessary risk notifications. The first type of report is an exception report. The purpose of an exception report is to list the exceptions, or risks, that were identified on each of the systems that were analysed. There will thus be an exception report for each individual mining site. The exception reports are configured to contain data from the previous day and the reports are generated daily.

The second type of report is a system-specific report. The purpose of the system-specific reports is to provide more detail regarding the operational risks on each subsystem. The system-specific reports are configured to contain data from the previous 30 days and are generated daily.

The data analysis is based on the newly-developed methodology (see Chapter 4). Python[1] was used for the software development of the calculation and reporting scripts, due to it being object oriented and open source. LaTeX[2] was chosen to typeset the reports due to it being based on text commands and could therefore easily be incorporated into the Python code. The whole data analysis and reporting process is fully automated. The new features that were developed are shown in Figure 5.6.

[1]Programming language – https://www.python.org/
[2]LaTeX Project Public License – https://www.latex-project.org//

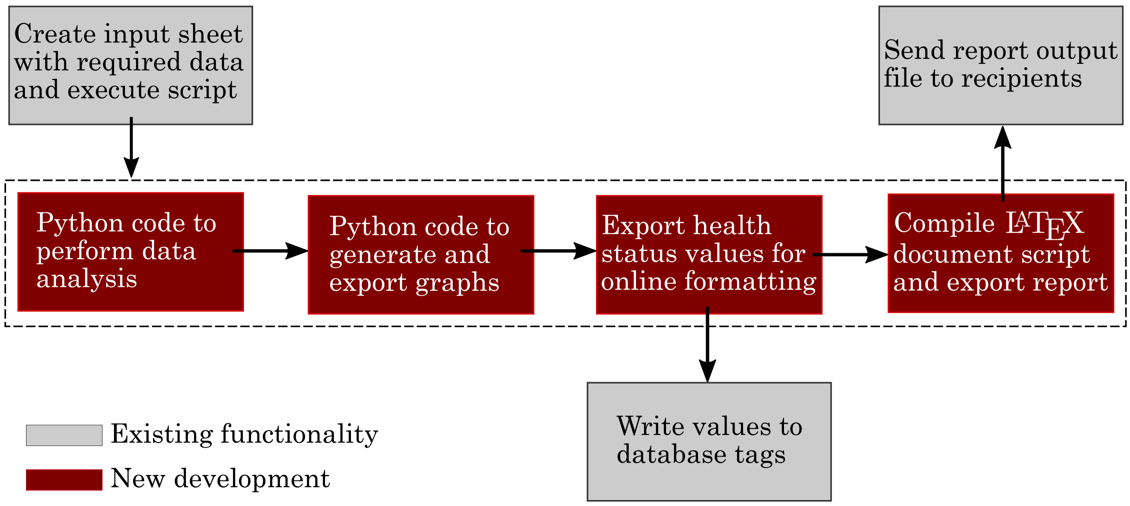


Figure 5.6: *Report generation process*

The analysis script imports the data from the input sheet and evaluates each parameter according to its respective limits. The user can specify the region limits on the report configuration sheet. Figure 5.7 shows an example layout of a compressor report's configuration sheet. The analysis is therefore performed on each individual column entry. The running status values represent each component's operational periods. It is only during periods of operation that the region totals are calculated. Parameter totals belonging to a corresponding parent (i.e. the relevant machine) can be added together to obtain a component total. The region totals are also used to calculate a risk score for each parameter.

Attributes	Compressor 1					Compressor 2					Compressor 3					Compressor 4				
Parameter	P1	P2	P3	P4	Pn	P1	P2	P3	P4	Pn	P1	P2	P3	P4	Pn	P1	P2	P3	P4	Pn
Tag name	T_{11}	T_{12}	T_{13}	T_{14}	T_{1n}	T_{21}	T_{22}	T_{23}	T_{24}	T_{2n}	T_{31}	T_{32}	T_{33}	T_{34}	T_{3n}	T_{41}	T_{42}	T_{43}	T_{44}	T_{4n}
Parent	C1	C1	C1	C1	C1	C2	C2	C2	C2	C2	C3	C3	C3	C3	C3	C4	C4	C4	C4	C4
Status Tag	S1	S1	S1	S1	S1	S2	S2	S2	S2	S2	S3	S3	S3	S3	S3	S4	S4	S4	S4	S4
Daily values	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48
Number of days	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30
Limit_S	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Limit_C	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Limit_R	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Limit_F	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•

Pn	-	Name of parameter n
T_{ij}	-	Tag name of component i, parameter j
C_k	-	Component k
S_k	-	Status tag of component k

Figure 5.7: *Configuration sheet for system-specific reports*

The exception report uses a similar configuration sheet. It does, however, contain multiple component types. Only a single day's data is assessed, as opposed to the 30 days that are used in the system specific reports. Critical and warning exceptions are listed in two separate tables, as shown in Figure 5.8. The exception report also contains an appendix where the daily profiles of the critical parameters are shown.

Summary of critical exceptions **2017-02-27**

A

Exception level: Critical			
Parameter	Critical limit	Violation duration (hours)	Violation period average
Comp 4 Compressor DE Vibr	5.4 mm/s	24	6.06
Comp 4 Compressor NDE Vibr	5.4 mm/s	4	5.99
FP2 Motor DE Temp	72 °C	15	73.46
Comp 3 Compressor NDE Vibr	5.4 mm/s	10	5.98
Comp 3 Compressor DE Temp	72 °C	1.5	74.03

Summary of warning exceptions

B

C

Exception level: Warning			
Parameter	Warning limit	Violation duration (hours)	Violation period average
Comp 4 Compressor DE Temp	62 °C	24	66.94
Comp 4 Gearbox NDE Temp	60 °C	24	61.87
Comp 4 Compressor NDE Vibr	5 mm/s	2	5.18
FP2 Motor NDE Temp	58 °C	24	67.81
FP2 Comp NDE Vibr	2 mm/s	11	2.27
FP2 Motor DE Temp	62 °C	9	71.34
FP2 Comp DE Vibr	2 mm/s	2	2.08
66L Pump 1 Motor NDE Temp	65 °C	16.5	66.84
66L Pump 7 Motor DE Vibr	2 mm/s	16.5	3.2
66L Pump 7 Pump DE Vibr	4.5 mm/s	16	4.86
66L Pump 7 Motor DE Temp	62 °C	12	70.02
66L Pump 7 Pump NDE Temp	45 °C	12	49.74
66L Pump 7 Motor NDE Temp	65 °C	11.5	68.81
66L Pump 7 Motor NDE Vibr	2.5 mm/s	11.5	2.8
Comp 3 Gearbox NDE Temp	60 °C	15	64.1
Comp 3 Motor NDE Temp	60 °C	7.5	61.27
Comp 3 Compressor DE Temp	62 °C	4.5	68.81
Comp 3 Compressor NDE Vibr	5 mm/s	1.5	5.23
66L Pump 3 Motor NDE Vibr	2.5 mm/s	14.5	3.33
66L Pump 3 Motor DE Temp	62 °C	13.5	64.22
66L Pump 3 Motor DE Vibr	2 mm/s	12	2.2
66L Pump 3 Motor NDE Temp	65 °C	1.5	65.02
FP3 Motor NDE Temp	58 °C	8	60.73
FP3 Motor DE Temp	62 °C	6	63.97
FP4 Motor NDE Temp	58 °C	5	59.97
66L Pump 6 Pump NDE Temp	45 °C	5	53.49
66L Pump 6 Pump DE Temp	62 °C	4	68.35
66L Pump 6 Motor NDE Temp	65 °C	2	69.87

Figure 5.8: *Sample of exception report layout*

These tables consist of four headings, which are: parameter, limit, violation duration and violation period average (marker A in Figure 5.8). The relevant limit that was exceeded is shown next to the violating parameter. The violation duration is the time period during which the parameter exceeded the limit. A violation period average is calculated by using all the values that have exceeded the given limit. The user can therefore determine the severity of each violation.

The table entries are sorted according to their violation duration, from high to low (marker B in Figure 5.8). This prioritises the high-risk parameters. The table entries are then grouped together according to the relevant component (marker C in Figure 5.8). This enables the user to evaluate all the risks on an individual piece of equipment.

More details regarding these violations are provided in the system-specific reports. These reports firstly provide the user with a seven-day overview of the relevant subsystems' operating regions. Figure 5.9 shows an example of a pumping system overview. The region totals are displayed as a percentage of the running count. The risk and failure totals, as well as the parameter contributions, are also added to the report.

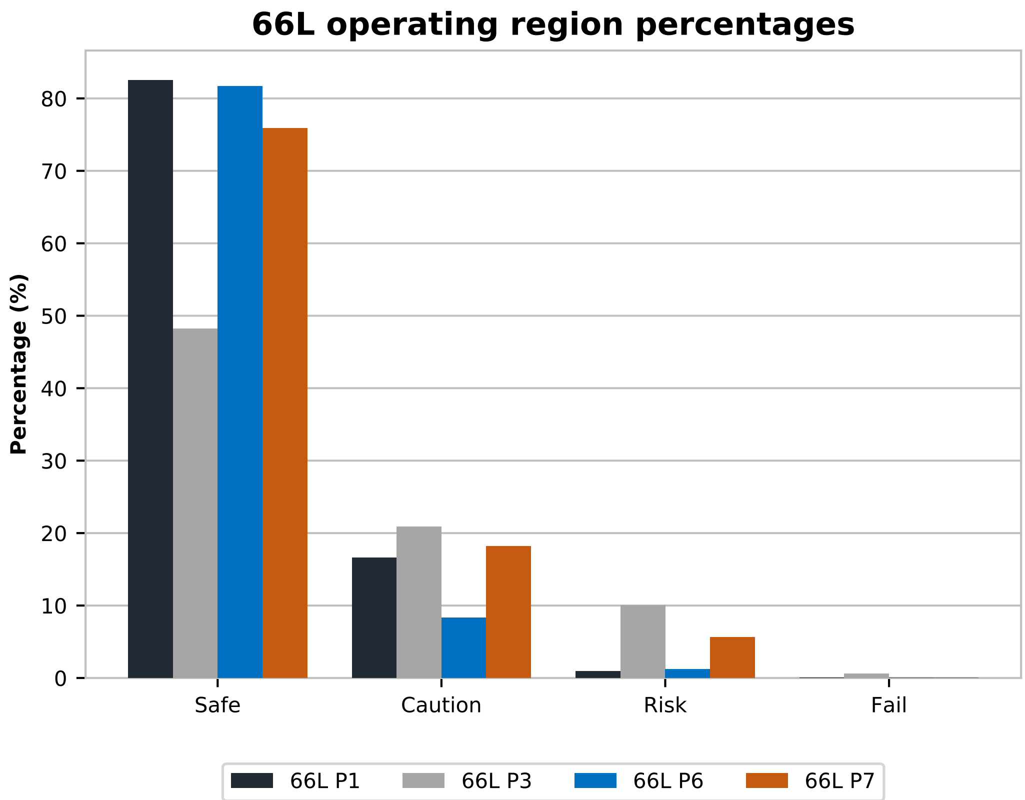


Figure 5.9: *Example of operating region overview*

Parameter values that are above or below the specified operating region limits, while the machine is operational, are categorised as invalid data. The invalid data count is included in the report and is also displayed as a percentage of the running count. Figure 5.10 shows that the *Pump NDE bearing temperature* on Pump 3 has an invalid data count of 100%. This indicates that the instrumentation probe needs to be examined.

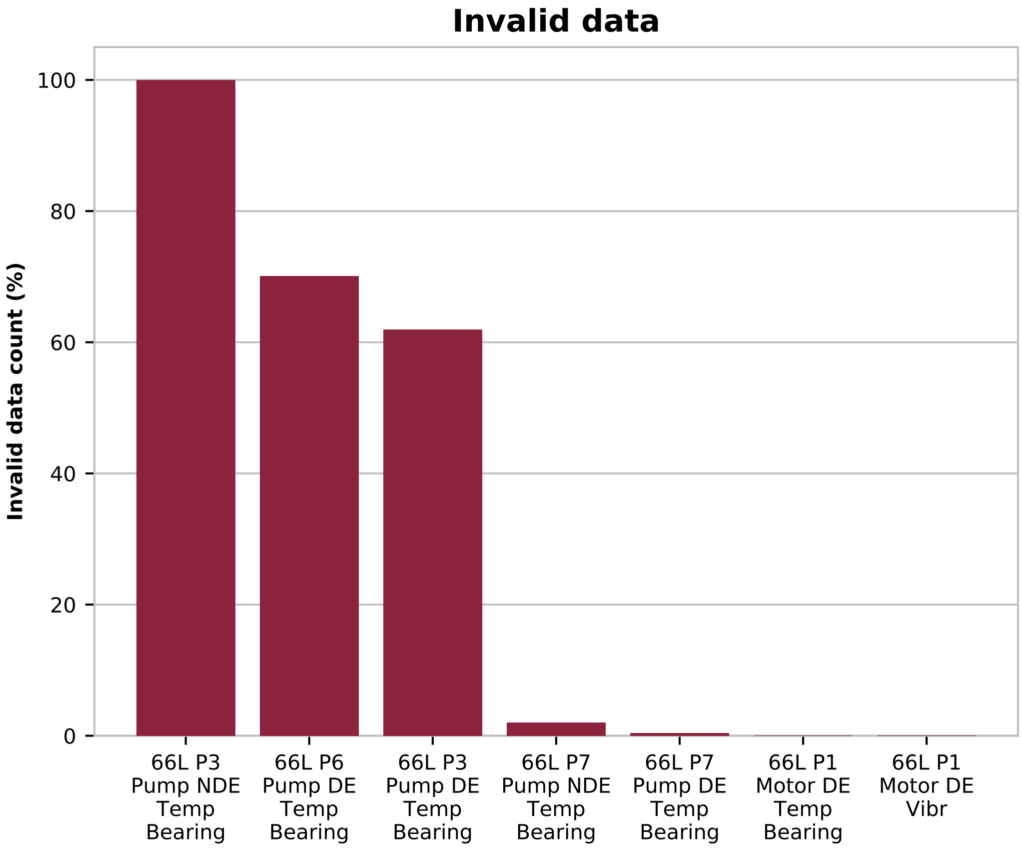


Figure 5.10: *Invalid data graph*

The system reports lastly provide the applicable risk analysis results. 30-day profiles of the region totals and risk scores are only shown for parameters in the medium- or high-risk category. The three risk categories are translated into a corresponding health status value. These status values are exported to database tags as daily totals. The online platform subsequently uses the health status tags to format the colour markers.

The final step in the report generation process is exporting the report document. A LaTeX document is generated and compiled to render a report with the necessary graphs and tables. Thereafter, the report is sent to the list of recipients.

Web interface

An essential part of the information system is providing users with access to operational data and the analysis thereof. The web interface, also referred to as the online platform, centralises information regarding the different mining systems. The relevant measurements or analysis results can be viewed by authorised users from any computer with an active internet connection. This means that supervisors can view any parameter's data for a given date without having to be on site, and manually perform the data extraction. The web interface gives users access to historical data and *live* data (see Figure 5.11) which is updated every 30 minutes.

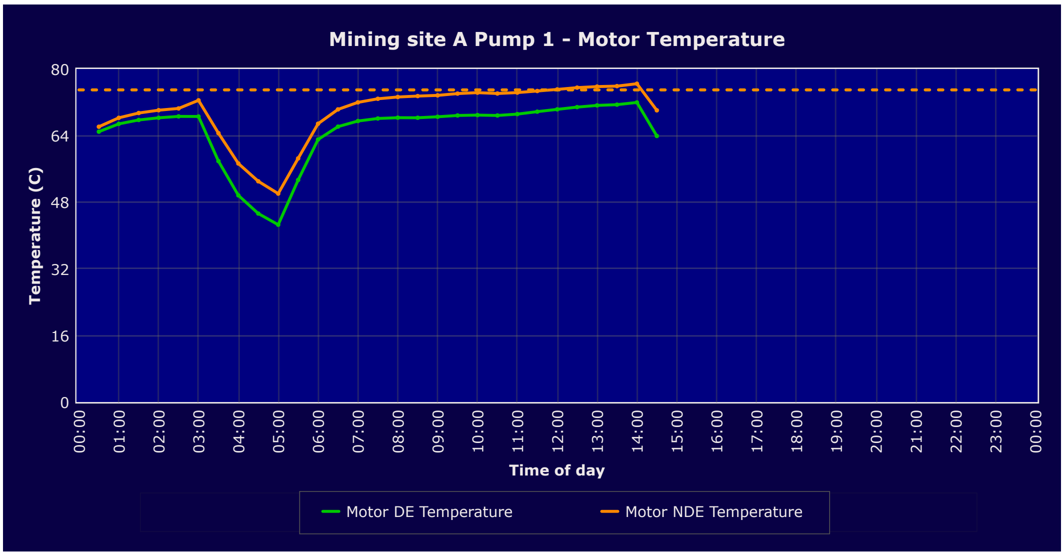


Figure 5.11: *Screenshot showing the live view of an example parameter*

The condition monitoring parameters are analysed daily. Results from the respective risk analyses are translated into health status values. Figure 5.12 illustrates how the parameter's risk category determines the health status value and the corresponding colour formatting.

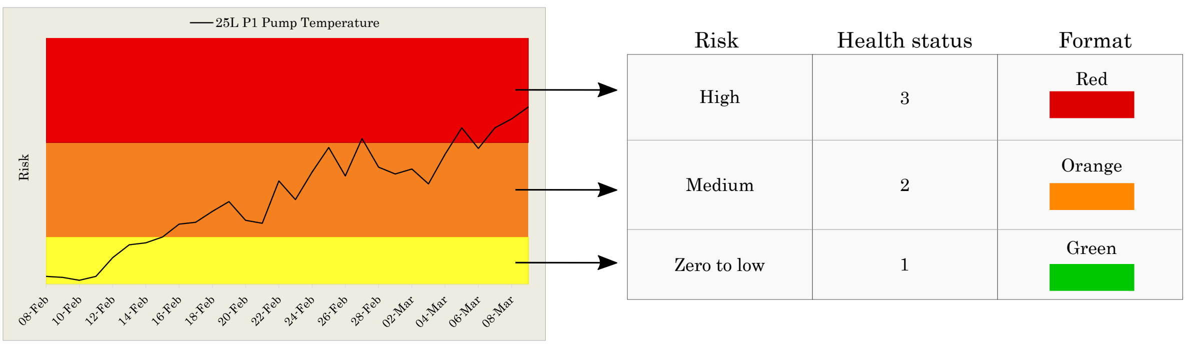


Figure 5.12: *Illustration of the relationship between risk categories and health indicators*

Parameters are grouped together, based on the type of measurement, to simplify the online display structure. A single formatting value can thus be assigned to each type according to the health status of the respective parameters. This is achieved by using the highest health status value from the input list.

Figure 5.13 demonstrates how two parameter types are formatted. The health indicator for temperature is coloured orange, due to a maximum health status value of two (2), as shown in Figure 5.13 (A). The health indicator for vibration is coloured red, due to a maximum health status value of three (3), as shown in Figure 5.13 (B). Each input list can be expanded to contain more parameters. The number of parameter types that are used can also be chosen according to the available input data.

Parameter	Health status	Format
Main Fan 1 - Fan DE Temp	1	Temp format: Main Fan 1 Orange
Main Fan 1 - Fan NDE Temp	2	
Main Fan 1 - Motor DE Temp	1	
Main Fan 1 - Motor NDE Temp	1	

(A)

Parameter	Health status	Format
Main Fan 1 - Fan DE Vibration	1	Vibration format: Main Fan 1 Red
Main Fan 1 - Fan NDE Vibration	1	
Main Fan 1 - Motor DE Vibration	3	
Main Fan 1 - Motor NDE Vibration	2	

(B)

Figure 5.13: *Formatting process of parameter types*

The same formatting procedure is followed for each mining system. Health indicators are updated daily for each subsystem within the relevant system. For example, an overview of a pumping system is shown in Figure 5.14.

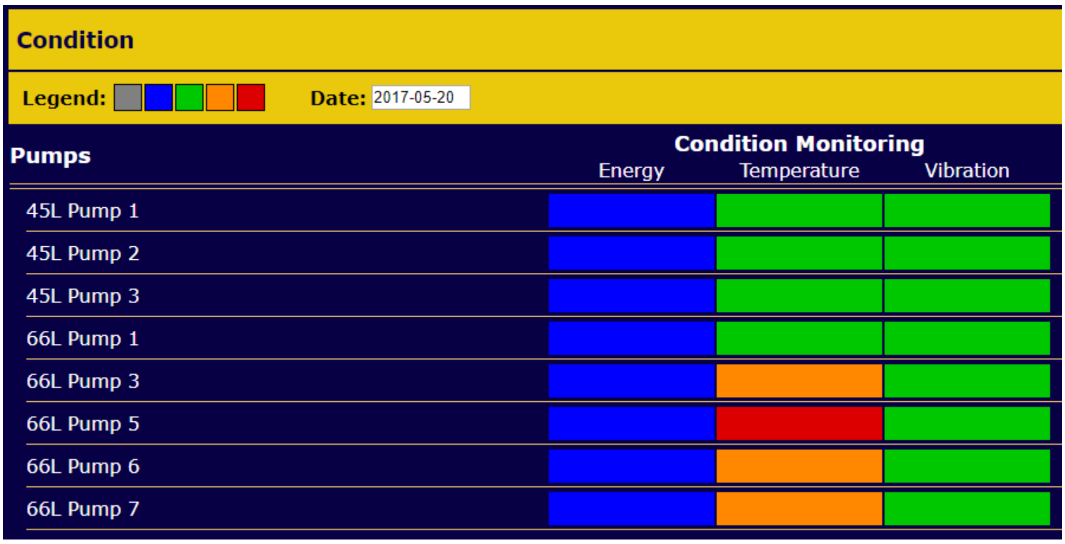


Figure 5.14: *Daily view of a pumping system dashboard*

Some parameter types are not compared to a limit setpoint and will therefore not display a coloured format. The blue markers, used in the energy column in Figure 5.14, indicate that formatting values are unavailable.

The health status of the respective subsystems is used to format the overall health indicator of each mining system. A bottom-up approach is therefore followed to provide the user with an overview of the entire operation. In this example, the user would navigate from the homepage dashboard (Figure 5.15) to the pumping system.

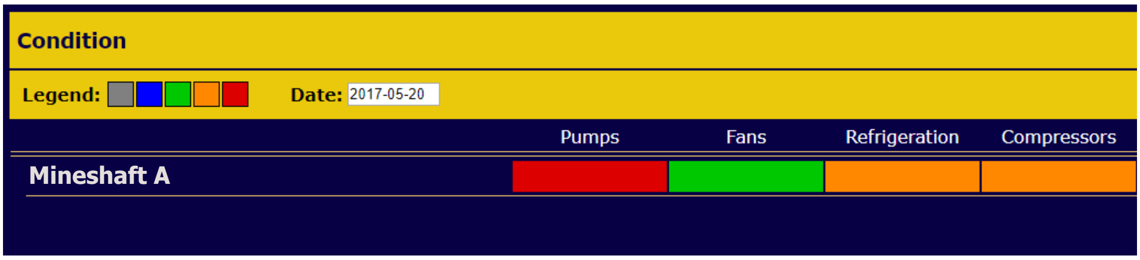


Figure 5.15: *Daily overview of a mining site*

The pumping system overview (Figure 5.14) indicates that temperature risks were identified on Pump 5. The user can therefore click the link in the temperature column of Pump 5 to view the relevant temperature parameters. This would display a dashboard that only contains the temperature parameters belonging to Pump 5 for the specified date. The third navigation step would provide the user with the profile of the at-risk parameter (Figure 5.16).

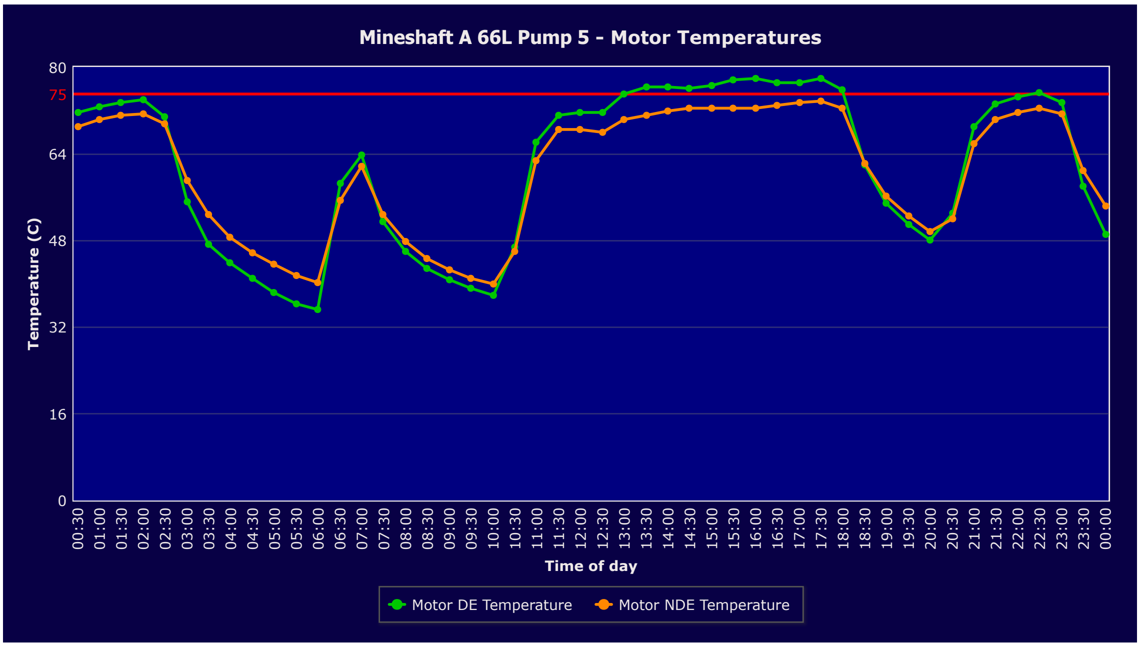


Figure 5.16: *Temperature profile of pump motor bearings*

The previous example illustrates how 64 pumping parameters (8 per pump) are analysed, grouped and displayed online. A similar approach is followed for the remaining mining systems. The simplified layout guides the user to the operational risks, without having to study each parameter individually.

5.4 Module verification

Preliminary operating limits were used to verify the alarms, reports and information displayed online. The aim was to confirm that the system feedback corresponds with the setup configuration. The verification procedure was therefore performed by implementing the system on a mining site. Notifications and reports were initially sent only to internal personnel. Although the information system was not fully operational on site yet, the evaluations consisted of actual machine- and process data.

Several alarms were configured on multiple types of mining equipment. The alarms were configured to send an alarm message to two recipients via email. The alarms were verified for a period of one month. Figure 5.17 shows an example of an alarm event.

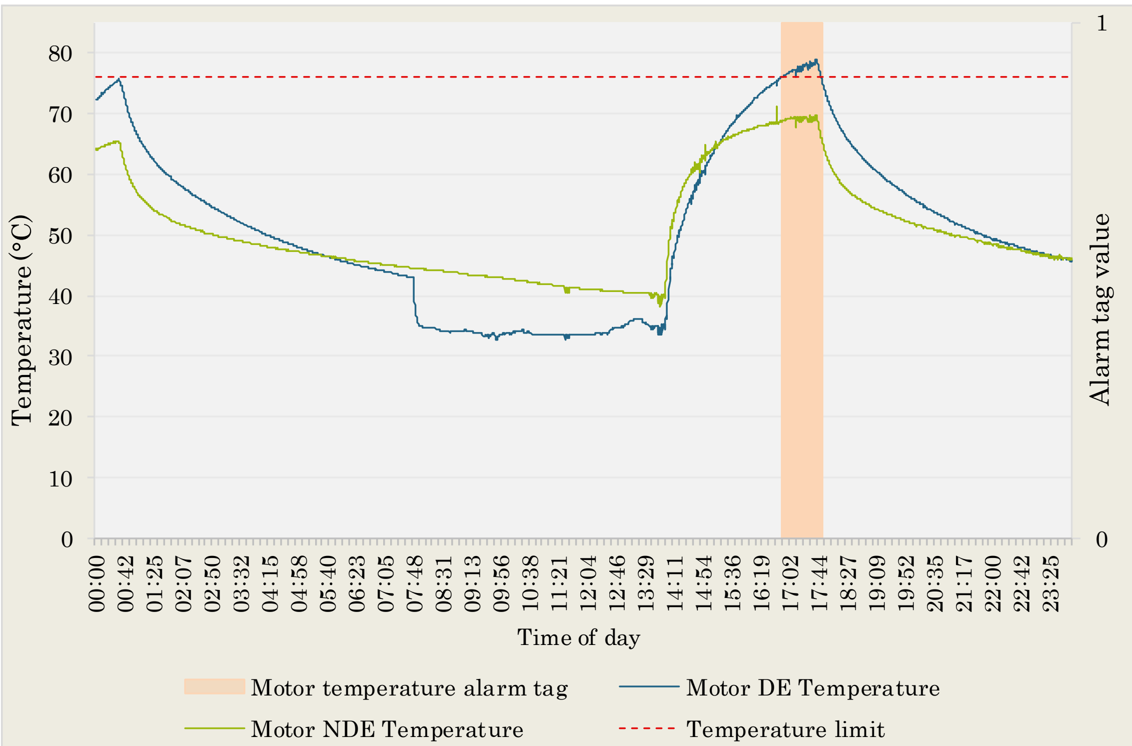


Figure 5.17: *Motor temperature alarm event*

Each alarm received was investigated to verify the parameter violation and the delivery of notifications. Alarms were only triggered during periods of machine operation. The temperature profile shown in Figure 5.18 is an example where the temperature measurement is above the limit, although the pump is switched off. This is due to maintenance, which means the high values are a result of the probes being removed and are not actual temperature readings. An alarm was therefore not triggered.

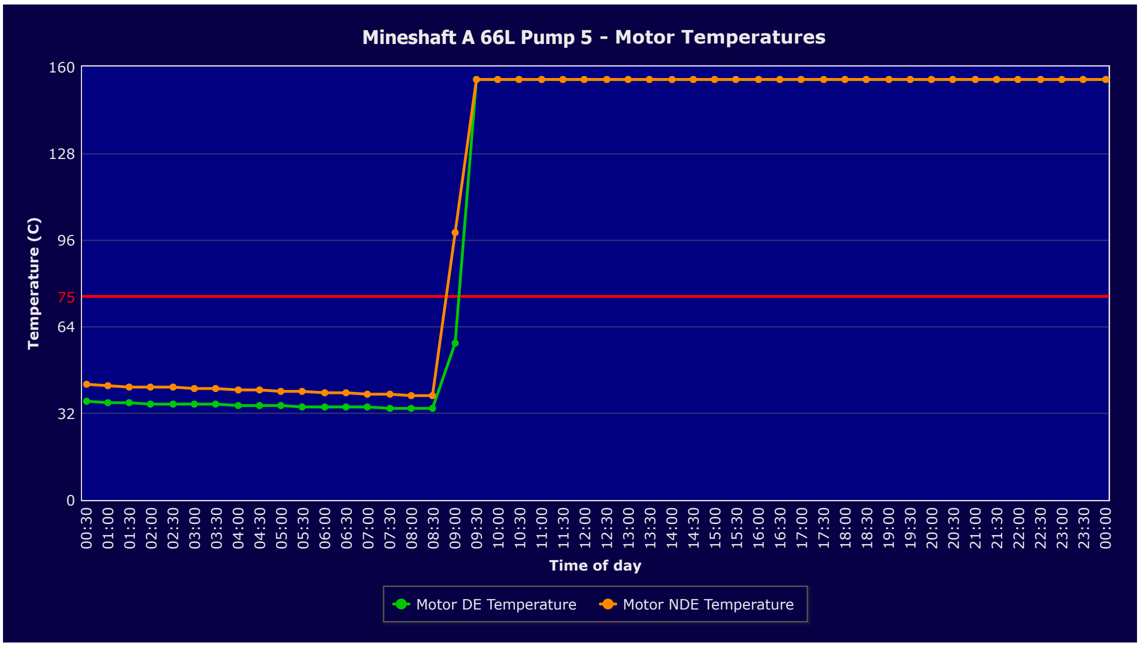


Figure 5.18: *High temperature reading caused by pump maintenance*

Table 5.1 shows a summary of the alarm verification figures. 22 alarms were triggered during the verification period. The alarm messages were sent to two recipients via email.

Table 5.1: *Alarm verification figures*

Alarms configured	Alarms triggered	False alarms	Emails delivered
60	22	0	44

The automated reports were also verified regarding accuracy and successful delivery. Table 5.2 contains report verification information for a period of 30 days. The exception report script and the system report script were verified in parallel. Days when the reports contained calculation errors, or when the reports were not generated and delivered successfully, are denoted in the table.

The master script errors were programming errors that needed to be fixed. These errors therefore affected all the reports that included the source code. Other errors were caused by volatile input data. Examples of this include missing data, or data not within the expected input range. Seeing as the system reports contain seven days' data and different calculation functions, it was possible that the relevant system report was affected, but not the exception report, and vice versa. Updates were made to the report scripts until the reports were verified to be accurate and robust.

Table 5.2: *Automated reports verification*

	Exception script	System script			
Report	Exception	Pump	Fan	Fridge	Compressor
01-Mar					
02-Mar	x				
03-Mar		x	x	x	x
04-Mar					
05-Mar	x		o		
06-Mar					o
07-Mar		o			
08-Mar	o				
09-Mar					
10-Mar					
11-Mar		x	x	x	x
12-Mar					
13-Mar	o	o			
14-Mar					
15-Mar					
16-Mar					
17-Mar					
18-Mar					
19-Mar					
20-Mar					
21-Mar					
22-Mar					
23-Mar					
24-Mar					
25-Mar					
26-Mar					
27-Mar					
28-Mar					
29-Mar					
30-Mar					

Legend

x	Master script error
o	Volatile input data

5.5 Summary

A mining operation comprises multiple systems and subsystems. These systems need to be available and operational for the mine to reach its production targets and maintain a safe working environment. It is vital for maintenance supervisors to regularly evaluate the current state of each system to determine where operational risks might exist. Different types of information management deliverables have therefore been developed to simplify the risk identification process.

Automated alarms were configured to notify personnel in real-time when parameters exceeded their safe operating limits. Notifications can be sent via email or SMS. Site personnel were only added to the recipient lists of the relevant mining system that they are involved with. Mining managers, however, received alarms from multiple mining sites. This enabled all the relevant stakeholders to be made aware of system risks pertaining to their area of responsibility.

Daily exception reports were developed to summarise the risk information. System exceptions are categorised as either critical or warning, depending on their risk score. The violation duration and violation period average are calculated for each parameter listed in the report. The system-specific reports provide more detail regarding the identified risks.

A web interface was used to provide multiple users with remote access to the system data and analysis results. Operational health indicators make it easy to determine where risks were identified. The user can also view selected parameter profiles over a chosen time period. In addition to historical data, the web interface provides users with a near real-time view that is updated every 30 minutes.

CHAPTER 6

Implementation and results

6.1 Preamble

A mining operation contains many moving parts, ranging from electrons to impellers. The continuous movement of these parts is vital to ensure that the mine remains profitable. It is therefore necessary to perform frequent maintenance investigations to prevent any of the moving parts from stopping unexpectedly or untimely. Equipment failure, or extended periods of non-operation, has a significant impact on a mine's production output and operating costs. Not only does healthy equipment yield financial benefits, it contributes to a safe working environment.

Equipment parameters such as pressure, temperature, current, flow rate and vibration should never exceed the design specifications. It is both inefficient and damaging when equipment operation violates the design boundaries. Machine- and process data were therefore monitored continuously. Automatic identification of anomalous or unsound equipment behaviour was key to effectively monitor an entire mining operation. Automated monitoring, together with information management, enabled maintenance supervisors to investigate the operational risks that were identified.

Figure 6.1 illustrates the various information management deliverables. The information system generates alerts, provides users with access to current and historical data and performs various data analysis procedures. Several types of parameters and multiple types of mining systems can be evaluated. The entire process has also been automated.

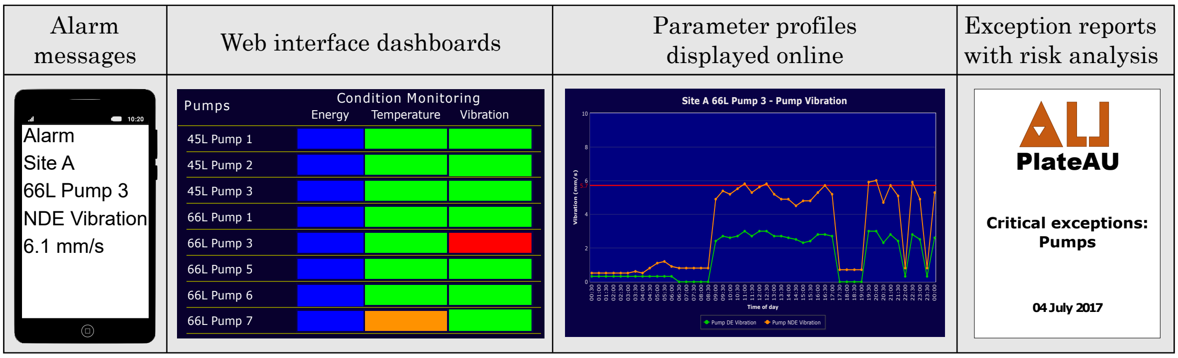


Figure 6.1: *Overview of the information management deliverables*

The information system was initially implemented on a single mining site consisting of four major mining systems: water reticulation, compressed air, ventilation and cooling. Data loggers were configured for each of these systems to log the required data. Alarms were configured to notify mine personnel of parameter violations. Data analysis scripts were developed to perform a daily SCRF analysis for each system and export the online formatting values to the respective database tags. Results from the analyses were compiled in exception reports and displayed on a web interface. The details of the initial implementation are compiled in Case study 1 (Mine A).

Following the success of the initial site implementation, the mining group requested that the system be implemented on five additional sites. Due to all four mining systems being available, as well as the large number of subsystems, Site 3 was selected for the second case study (Mine B). Figure 6.2 illustrates the scope of the six site implementations. The mining systems and the number of subsystems that were evaluated are listed below each site.

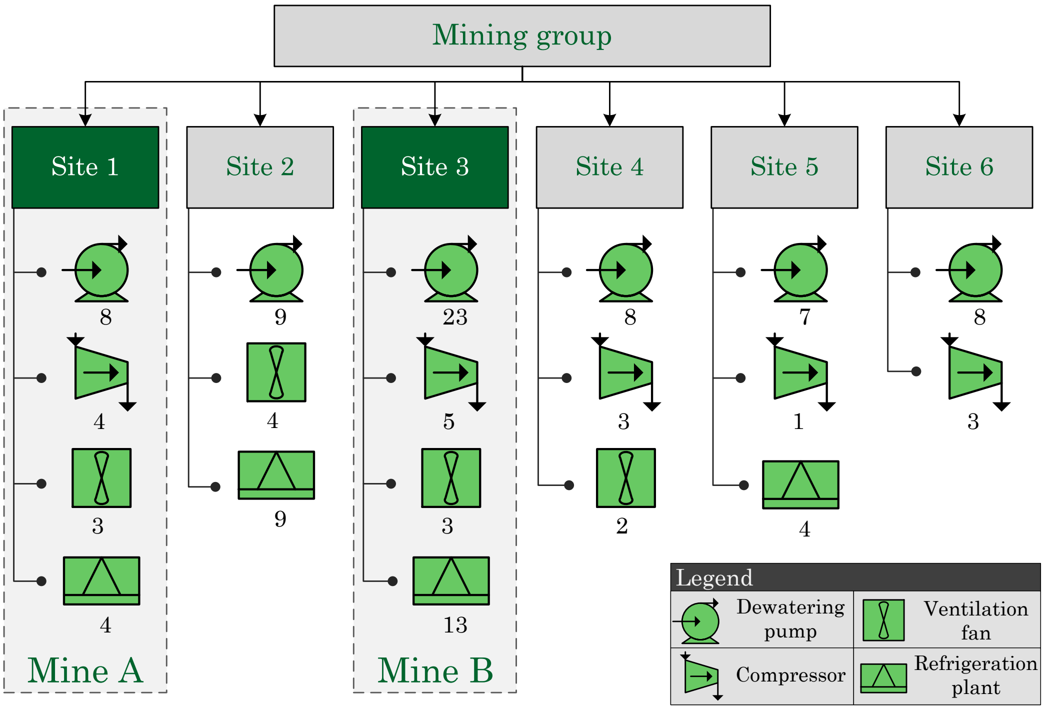


Figure 6.2: *Scope of the six site implementations*

A screenshot of the online platform's overview page can be seen in Figure 6.3. The system configurations were performed according to the availability of instrumentation.

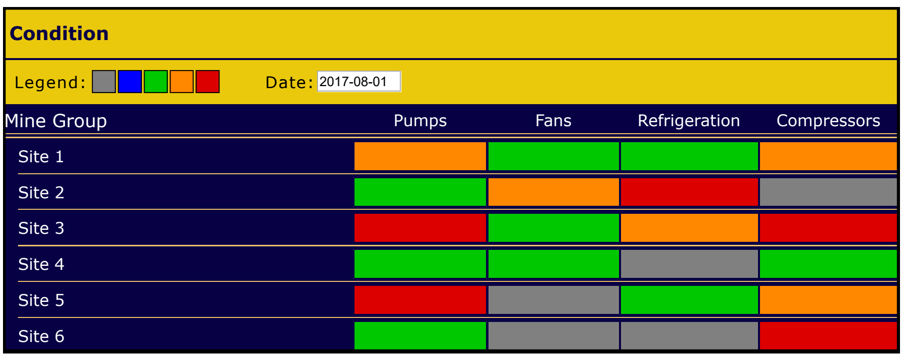


Figure 6.3: *Online platform overview page*

6.2 Overview of the validation process

The value of the information system was proven with the assessment of various types of mining equipment across several sites. Daily evaluations of the equipment's operational condition were performed automatically. An innovative risk analysis was used to identify operational risks within each mining system. These risks were conveyed to the relevant stakeholders via different types of communication media. The information system was subsequently incorporated into the mine's maintenance strategy.

Two mineshafts were selected to be used as case studies. Due to confidentiality, these mines are referred to as Mine A and Mine B. The details relevant to each case study have been structured according to the layout shown in Figure 6.4. Firstly, the site specifications are listed. This demonstrates the scope of the operation. Secondly, the implementation details provide information regarding the system configuration. Lastly, the results from the assessment are discussed.

Site specifications
Mine location
Maximum mining depth (km)
Cash operating cost (R/kg)
Implementation details
Installed equipment
Input tags
Format tags
Alarms configured
Reports
Assessment results
Operational risks identified
Risk validation and remedial action
Assessment overview

Figure 6.4: *Case study evaluation criteria*

Although similarities exist, regarding the site implementations, each site is unique. The implementations were therefore preceded by several meetings to discuss the available infrastructure, alarm limits and notification strategy.

Alarms were used to generate real-time risk alerts. Mining personnel, as well as mining management, received SMS notifications when parameter values exceeded the alarm limit set point for a period of five minutes. False alarms are generated if the set points are too low. Correspondingly, operational risks go unnoticed when the set points are too high. Mining technicians therefore confirmed the trip limits for all the systems, which could be used to determine suitable alarm limits.

Alarm limits, for the respective site's equipment, were proposed by each individual site. Once approved by management, the site's configuration was finalised accordingly. The alarm limits also determine when the input values are classified as a warning or critical exception, on the online platform and in the reports. Each parameter's failure region limit was set to correspond with the alarm limit. The warning region limits were chosen according to an acceptable margin below the alarm limit.

The notification strategy is a vital element of each implementation. Recipients were added to specific SMS alarms, system-specific reports and exception reports, as requested by the mine. The mining management personnel were added to the distribution list for all of the sites' exception reports and, in some cases, SMS alarms. Engineering managers, each responsible for a specific site, were added to the distribution list of the relevant site's exception report and SMS alarms. System engineers and foremen were added to the distribution list of the relevant system's SMS alarms and system-specific reports.

The system was designed to make future expansion possible. Bearing temperature and vibration were used as the initial parameter types to validate the analysis process. Multiple mining systems were assessed according to these parameter types, due to these values being readily available. It was therefore not necessary to install and commission any additional sensors. A user can, however, configure additional types of equipment and parameters, each with specific operating limits. This means the system was validated to be accurate, scalable and customisable.

6.3 Case study 1: Mine A

Mine A forms part of the mining group's southern operations. Table 6.1 lists the site specifications.

Table 6.1: *Mine A – Site specifications*

Specification	Mine A
Mine location	South Africa
Maximum mining depth	> 2 km below surface
Cash operating cost (R/kg)	> 300 000

Implementation details

Figure 6.5 shows an overview of the implementation. The illustration indicates the number of subsystems and the corresponding number of input tags that were used, for each of the four main systems. 60 alarms were configured to send SMS alerts to four mine employees. A total of 218 input values were received and translated every 30 minutes. 114 online formatting tags were updated daily to indicate where risks have been identified. 150 exception reports were compiled and 360 emails were delivered over a 30-day period.

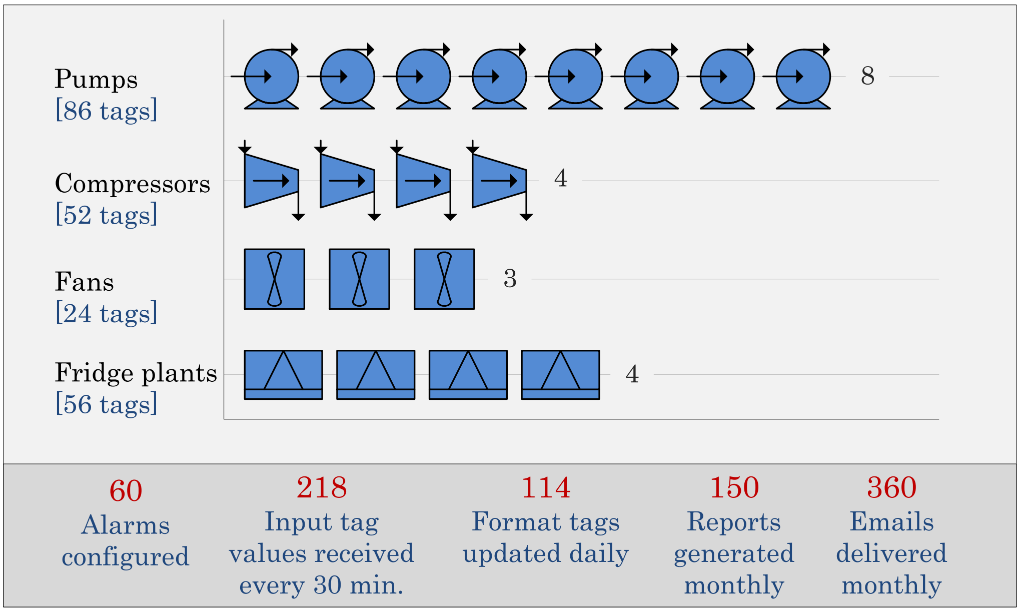


Figure 6.5: *Mine A – Overview of implementation*

The system reports are generated on a daily basis. Each system report performs a data analysis on the incoming data. The data analysis procedure calculates a risk score for each of the input parameters. The risk scores are translated to health statuses, which are exported to the respective format tags. All the subsystems, together with the corresponding input and format tags, were configured on the online dashboards. Table 6.2 lists the input parameters that were used in the evaluation. Certain parameters were not available for all of the subsystems.

Table 6.2: *Mine A – Input tag parameters*

Pumps	Compressors	Fans	Fridge Plants
Motor DE[1] vibration	Motor DE vibration	Motor DE vibration	Motor DE vibration
Motor NDE[2] vibration	Motor NDE vibration	Fan NDE vibration	Motor NDE vibration
Pump DE vibration	Compressor DE vibration	Motor DE temperature	Compressor DE vibration
Pump NDE vibration	Compressor NDE vibration	Motor NDE temperature	Compressor NDE vibration
Motor DE temperature	Gearbox vibration	Fan DE temperature	Gearbox vibration
Motor NDE temperature	Motor DE temperature	Fan NDE temperature	Motor DE temperature
Pump DE temperature	Motor NDE temperature	Guide vane angle	Motor NDE temperature
Pump NDE temperature	Compressor DE temperature	Motor current	Evaporator temperature in
Motor power	Compressor NDE temperature		Evaporator temperature out
Suction pressure	Gearbox DE temperature		Condenser temperature in
Discharge pressure	Gearbox NDE temperature		Condenser temperature out
	Gearbox Thrust DE temperature		Evaporator flow
	Gearbox Thrust NDE temperature		Condenser flow
			Motor power
[1]Drive end (DE) [2]Non-drive end (NDE)			

The following figures show the various dashboards of Mine A. Each figure shows the current state of the system on an arbitrary day to illustrate the system implementations.

Figure 6.6 shows the compressed air dashboard of Mine A. The compressed air system comprises four compressors with rated capacities exceeding 3 MW.

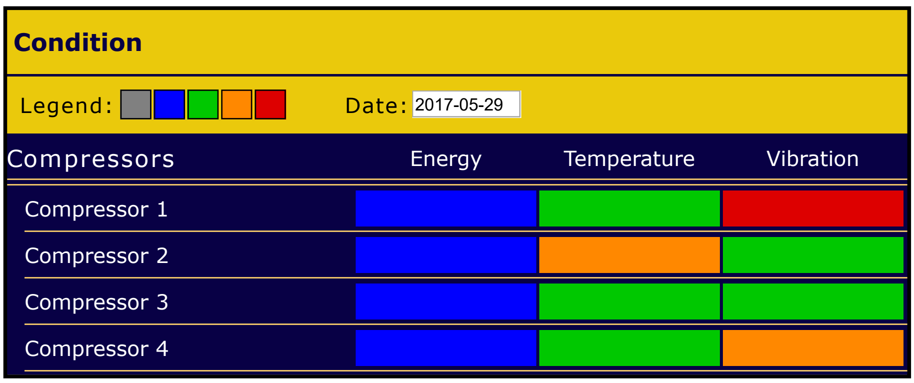


Figure 6.6: *Mine A – Overview dashboard of the compressed air system*

Figure 6.7 shows the water reticulation dashboard of Mine A. The water reticulation system consists of eight dewatering pumps, located on two different mining levels.

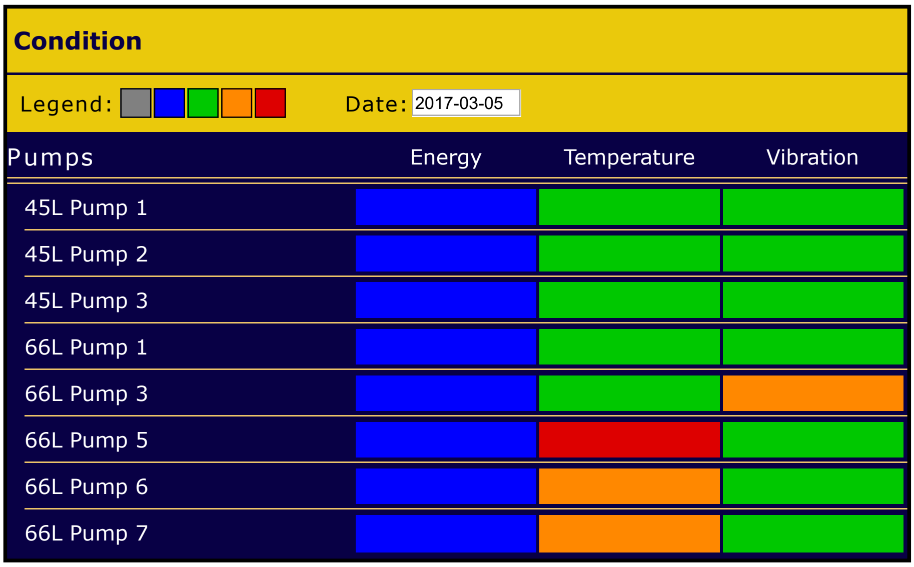


Figure 6.7: *Mine A – Overview dashboard of the water reticulation system*

Figure 6.8 shows the refrigeration dashboard of Mine A. Four 1 MW refrigeration plants are used to provide the mining operations with cold water.

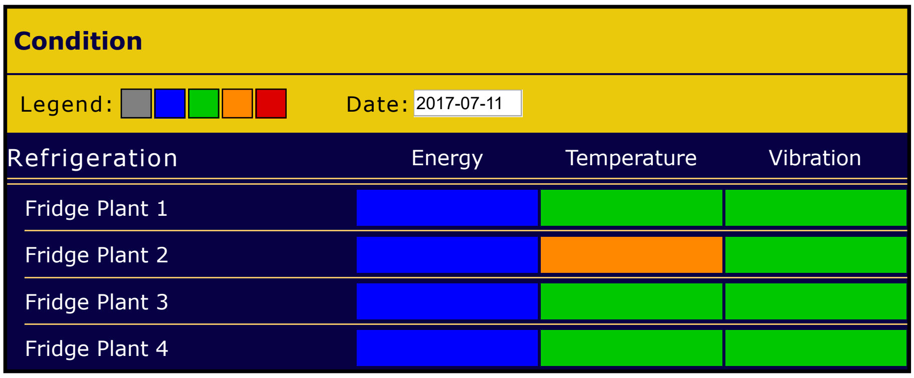


Figure 6.8: *Mine A – Overview dashboard of the cooling system*

Figure 6.9 shows the ventilation dashboard of Mine A. The three fans are located on the surface of the mineshaft.

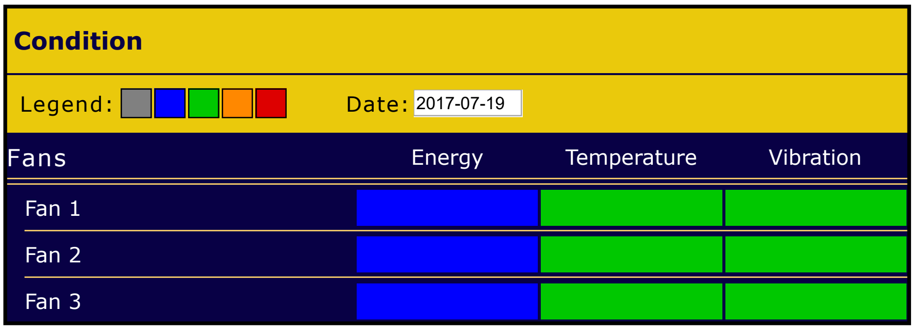


Figure 6.9: *Mine A – Overview dashboard of the ventilation system*

Assessment results

The majority of the operational risks that were identified, occurred on the dewatering pumps. One pump in particular displayed ongoing and various types of failure symptoms. The initial feedback indicated that the pump's operation was normal, seeing as these irregularities had been observed since the commissioning of the pump. Nevertheless, the mining management requested that maintenance professionals perform a visual inspection to determine whether the pump needed to be serviced. The findings indicated that the coupling gap was insufficient and that the pump and motor were misaligned. These defects were attributed to an incorrect installation.

Operational risk identification

Several types of operational risks were identified by the system analyses. These risks were conveyed to the mining personnel according to the agreed-upon notification strategy. The first form of communication was the alarm notifications. Respective personnel received an email or SMS message when an input parameter exceeded the alarm limit for more than five minutes. This made the managers aware of equipment that regularly violated the safety specifications.

The awareness that was created by the alarm notifications had a positive impact on the number of alarms that were triggered. Figure 6.10 displays the number of unique parameters that triggered an alarm during a 60-day period. There was a definite decrease in the number and frequency of alarms that were generated.

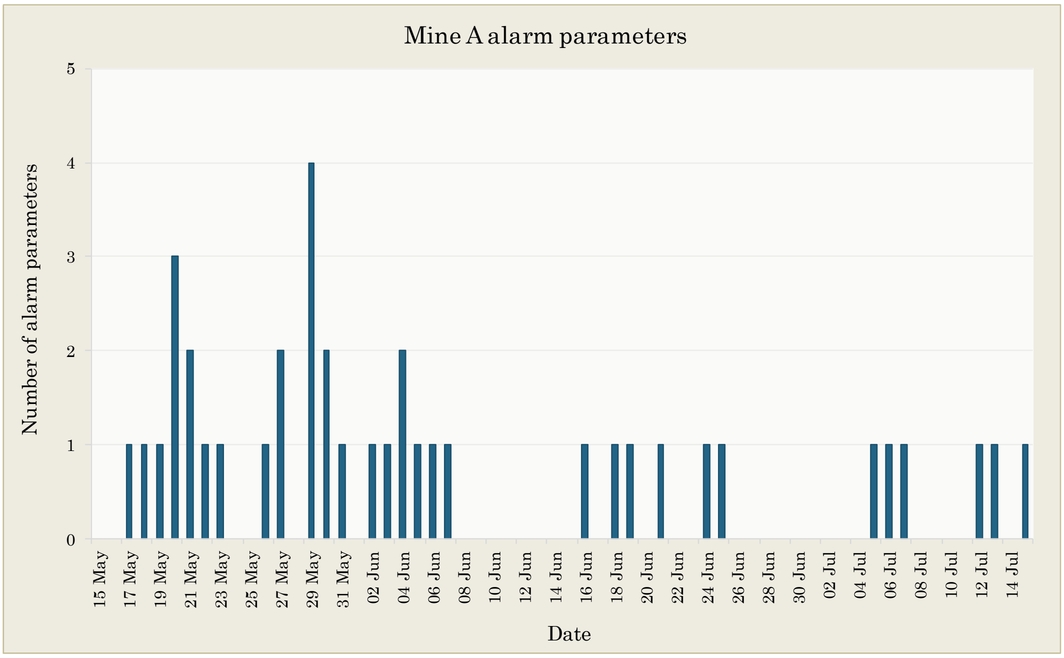


Figure 6.10: *Mine A – Number of alarm parameters*

The exception reports summarise the high- and medium risk parameters. These reports indicated that the NDE bearing temperature on the motor of 66L Pump 5 continuously exceeded the critical limit. An excerpt of one of these reports can be seen in Figure 6.11. On this specific day, the temperature exceeded the limit of 75°C for a period of five hours. The average temperature during this period was 77.5°C.

Summary of critical exceptions

Parameter	Critical limit	Violation duration (hours)	Violation period average
66L P5 Motor NDE Temperature	75.0°C	5	77.5°C
FP 2 Motor DE Temperature	75.0°C	4	75.4°C

Summary of warning exceptions

Parameter	Warning limit	Violation duration (hours)	Violation period average
66L P3 Motor NDE Vibration	3.3 mm/s	18	3.6 mm/s
Comp 3 Gearbox NDE Temperature	62.0°C	11.5	65.6°C
FP 2 Motor NDE Temperature	65.0°C	3.5	68.6°C
66L P1 Motor NDE Temperature	70.0°C	2	72.5°C

Figure 6.11: *Mine A – Example of an exception report*

The exception report also includes the daily profiles of the critical parameters. The motor temperature profile can be seen in Figure 6.12. Sharp temperature increases were observed when the pump was switched on. It was therefore continuously operated in a run-to-trip fashion. This type of cycling operation, coupled with high bearing temperatures, is considered to be destructive and undesirable.

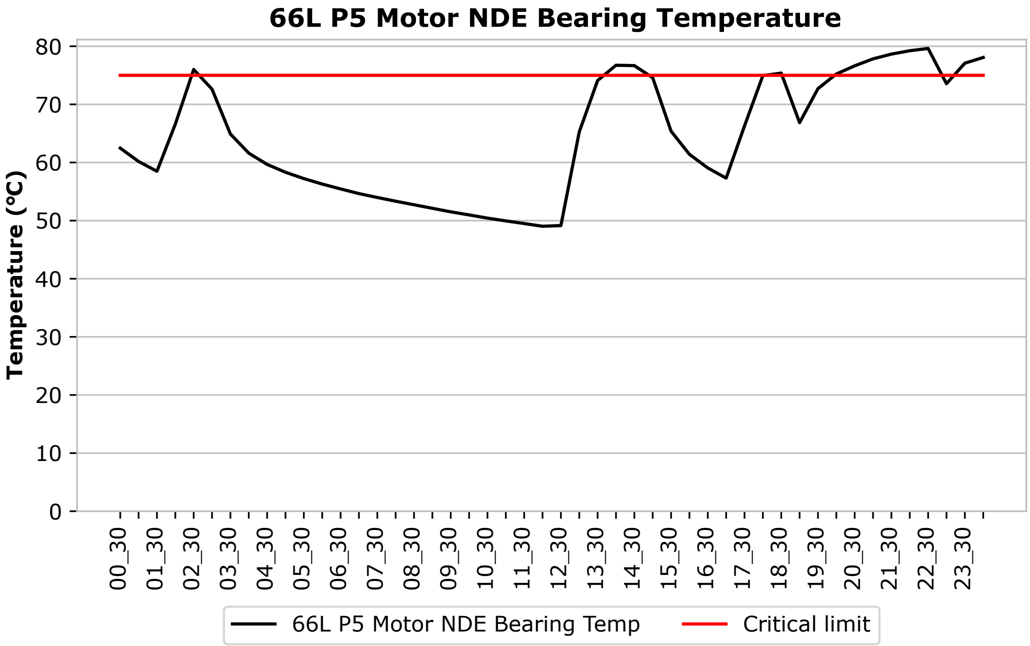


Figure 6.12: *Mine A – Exception report parameter profile*

The input parameters of each subsystem (e.g. Compressor 1) were analysed daily according to the SCRF methodology. A weekly total was subsequently calculated for each individual parameter, followed by each subsystem. The system reports only contain the six subsystems with the highest risk and failure region totals. The contents of the pump-specific report will be used here to illustrate the system analysis.

Figure 6.13 shows the six pumps which were determined to be the highest risks for the specific time period. It is evident from the graph that 66L Pump 5 needed attention. 66L Pump 5 exhibited a failure region total of 55 and a risk region total of 32. These totals comprise the individual pump parameter totals. The next step was therefore to examine the individual parameter distribution.

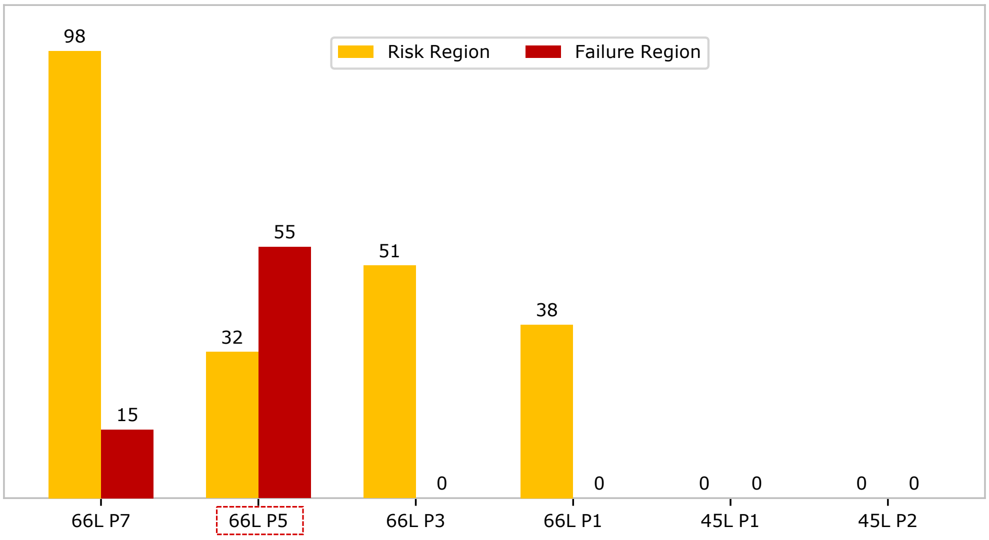


Figure 6.13: *Mine A – Pump risk and failure region totals*

The parameter distribution coincided with the findings of the exception report. Figure 6.14 displays the individual failure region counts of the parameters relating to temperature. The main contributor towards the failure region total was the NDE bearing temperature on the motor associated with 66L Pump 5.

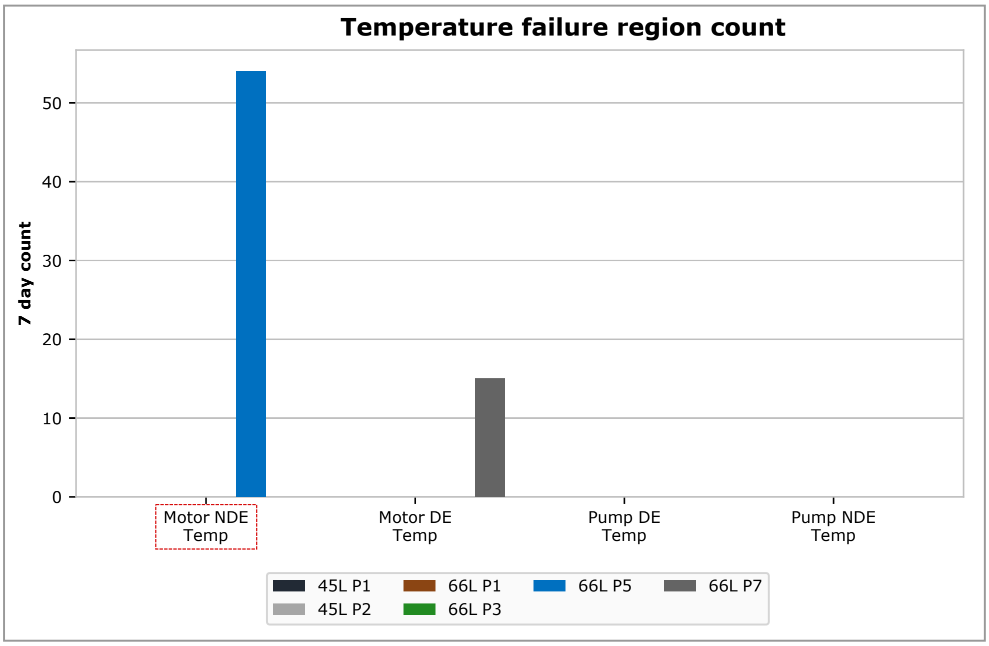


Figure 6.14: *Mine A – Failure region totals of temperature parameters*

The pump-specific report also indicated that 66L Pump 5 displayed risks relating to vibration. More than half of the pump's risk region total was attributed to the motor DE vibration (Figure 6.15).

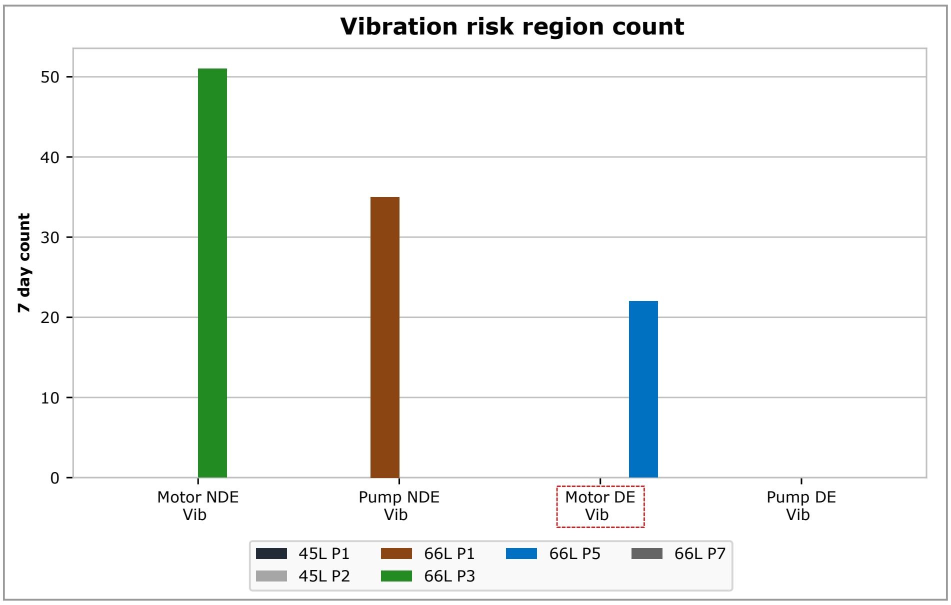


Figure 6.15: *Mine A – Risk region totals of vibration parameters*

Also included in the system-specific reports are the 30-day risk analysis and region total profiles. Figure 6.16 shows that the motor temperature was constantly in the high-risk region. This was a clear representation of the unhealthy operational condition of the relevant pump. Although not as severe at first, the motor vibration also exhibited signs of unsound operation. Figure 6.17 shows the risk profiles of the motor vibration for a three-month period. The profiles illustrate how the risk score progressed from the low-risk- to the high-risk region. This validates the fact that the system warnings need to be monitored and investigated before it develops into a serious issue.

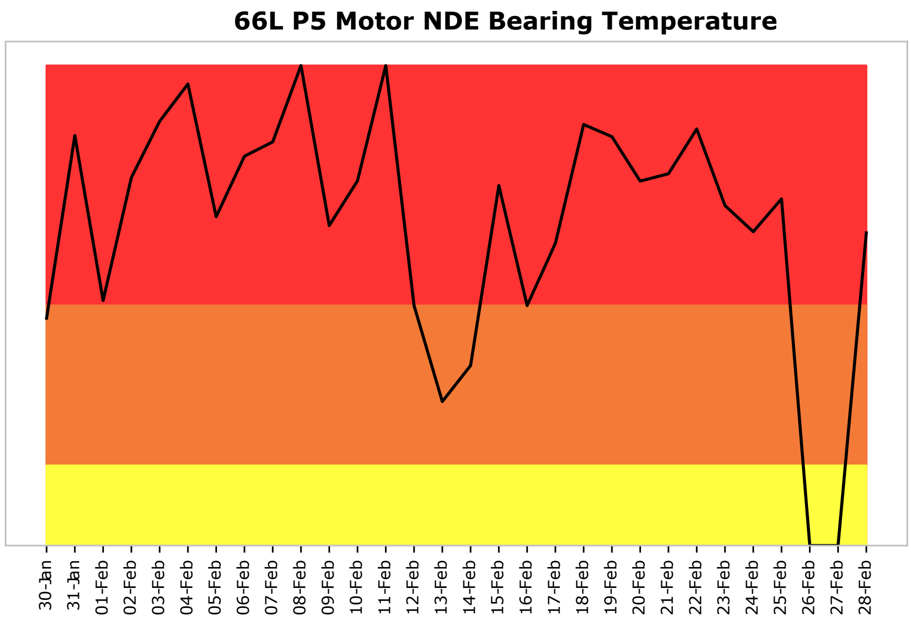
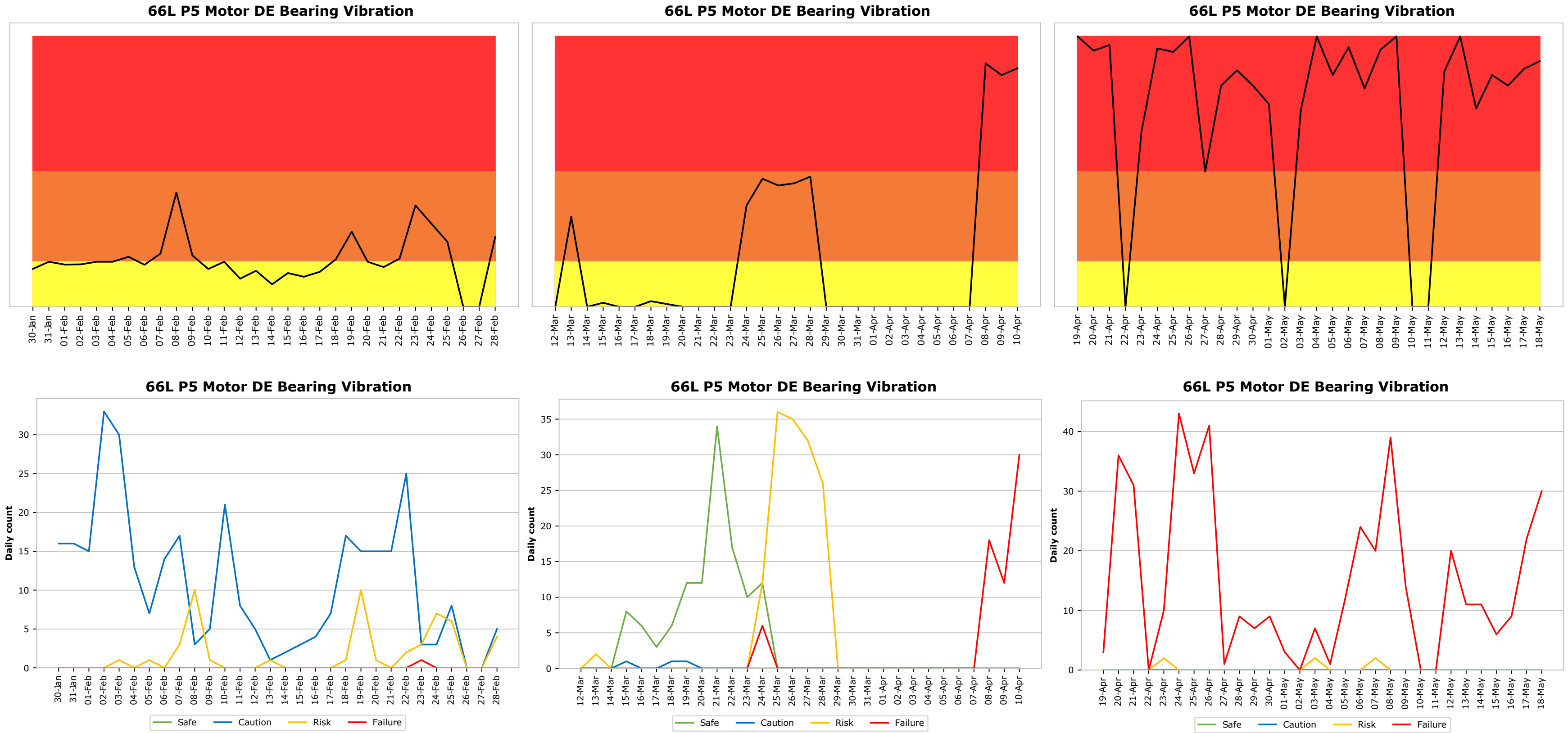


Figure 6.16: *Mine A – Risk score profile of motor NDE temperature*



(A) (B) (C)

Figure 6.17: *Mine A – Three-month risk score profiles of motor DE vibration*

Another type of operational risk that can be detected by the data analysis procedure is invalid or suspect data. Measurements that do not comply with the specified regions of operation are classified as invalid. Figure 6.18 shows that the pump temperature measurements associated with 66L Pump 5 were considered to be invalid. The invalid count percentage was 100%. This was due to the fact that the pump temperature was below the lower limit while the pump was operational. The relevant instrumentation was subsequently investigated.

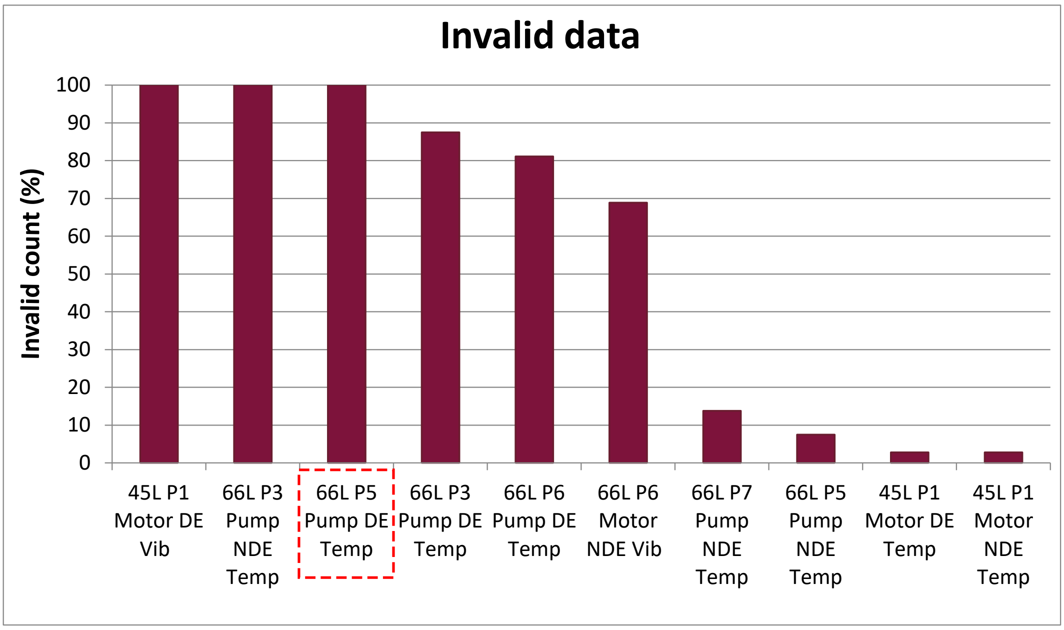


Figure 6.18: *Mine A – Invalid data analysis*

Risk validation and remedial action

The risks that were previously discussed were investigated by maintenance personnel. Their findings indicated that corrective action was needed, which resulted in the scheduling of the required maintenance. The parameter profiles that are shown here were obtained from the web interface. These profiles illustrate how the equipment was restored to a healthy condition, and therefore validate the risk analysis procedure.

The parameters that are shown here were measured on 66L Pump 5. Due to the high risk score, the motor temperature was addressed first. Figure 6.19 shows the motor temperature profile which corresponds with the risk analysis shown in Figure 6.16. The chart on top displays the running status of the pump, which is illustrated by the motor power. It is evident that the temperature exceeded, or approached, the alarm limit of 75°C when the pump was operational. This resulted in the pump regularly tripping.

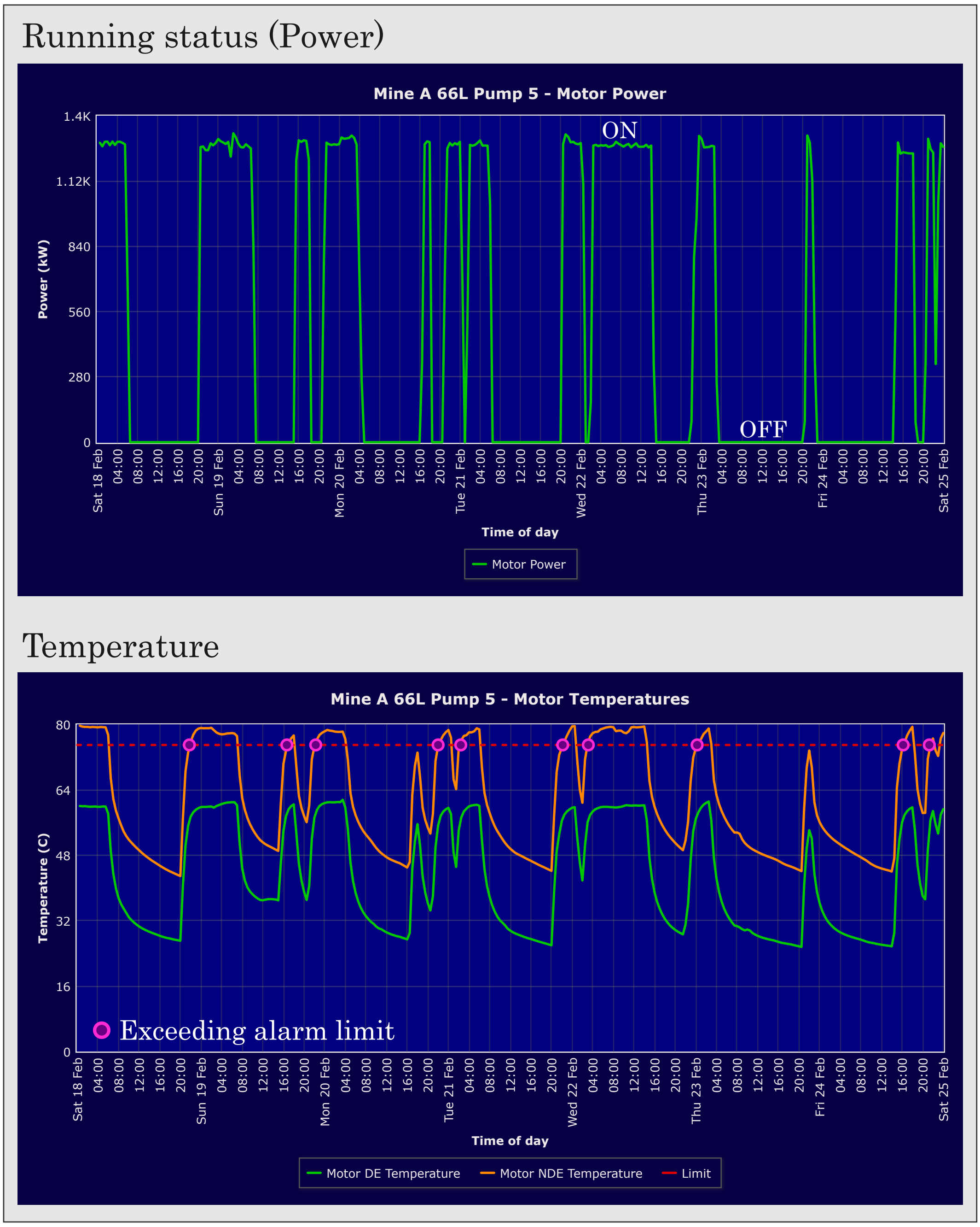


Figure 6.19: *Mine A - Initial parameter profile of temperature exceeding alarm limit*

A visual inspection was scheduled to examine the pump and motor. The quality surveillance report indicated that the rotor thrusted on the bearing. In addition to this, the coupling gap was 2 mm instead of the required 8 mm. The motor was therefore moved away from the pump and the coupling gap was corrected. Figure 6.20 shows the status and the temperature profiles after the pump was serviced. It can be seen that the temperature no longer exceeds the 75°C alarm limit.

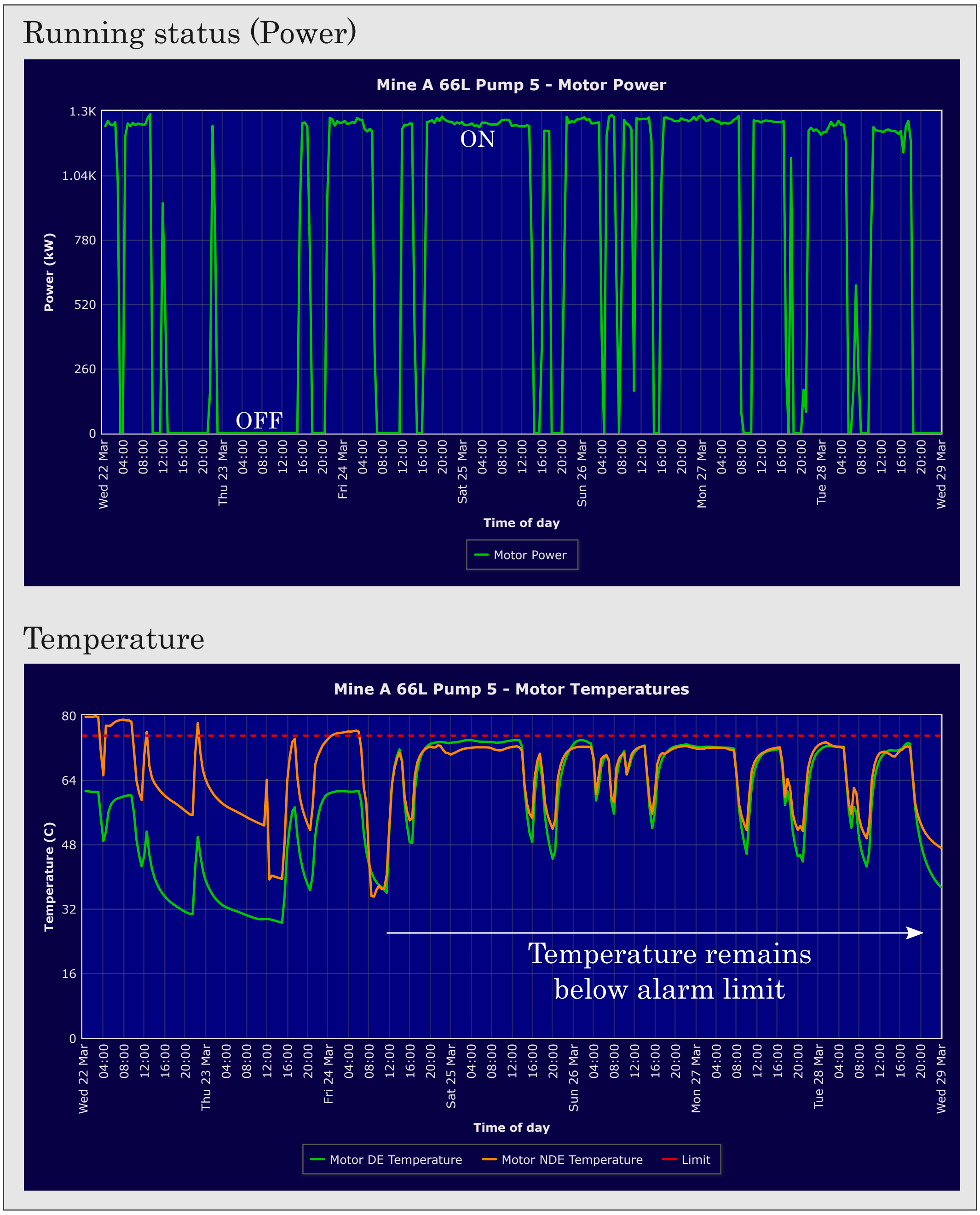


Figure 6.20: *Mine A - Weekly profile of temperature measurements following repair work*

The motor vibration progressed from the low-risk- to the high-risk region over a period of time. Figure 6.21 shows the motor vibration profile which corresponds with the risk analysis shown in Figure 6.17 (C). The status is shown in the top chart and demonstrates that the vibration exceeded the alarm limit of 4 mm/s during periods of operation. Although the high vibration values did not yet exceed the trip limit of 6 mm/s, it was deemed necessary to rectify the problem.

Figure 6.21: *Mine A - Initial parameter profile of vibration exceeding alarm limit*

The vibration was due to the pump and motor being misaligned. The pump and motor were therefore re-aligned and the magnetic centre was re-established. Figure 6.22 displays how the vibration remains below the 4 mm/s alarm limit. This was an example of how the information system enabled CBM and prevented probable future damage.

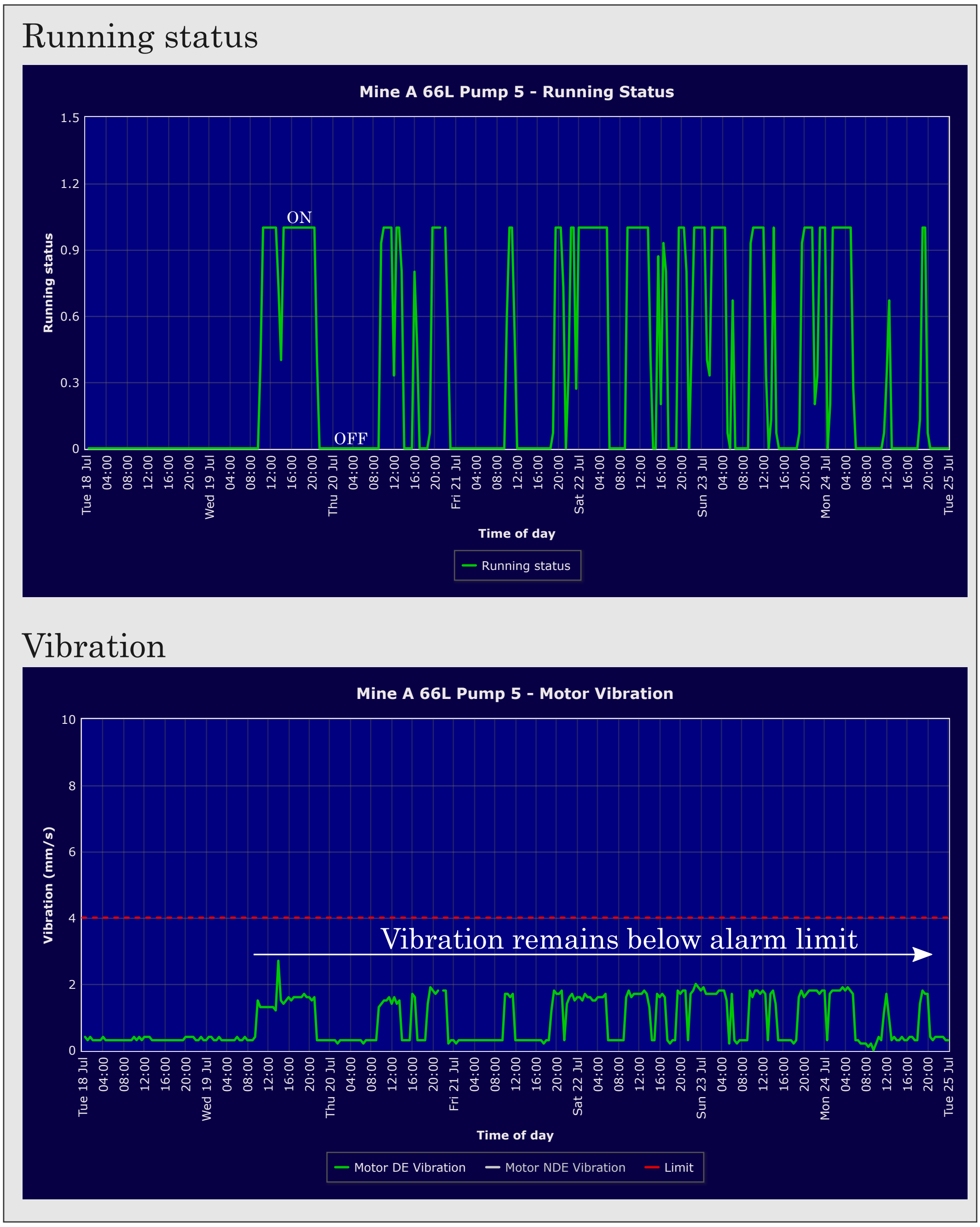


Figure 6.22: *Mine A - Weekly profile of vibration measurements following repair work*

The high invalid data count, as identified by the analysis procedure, was a result of the pump DE bearing temperature remaining low while the pump was operational. The actual pump temperature was therefore not being correctly measured. This could potentially be a major safety risk and cause serious damage. Figure 6.23 shows the pump DE and NDE temperatures. It is clear that only the NDE temperature measurement was functional. During periods of operation, the DE temperature remained low and the temperature difference (ΔT) was too large. The two temperature profiles should ideally follow each other more closely.

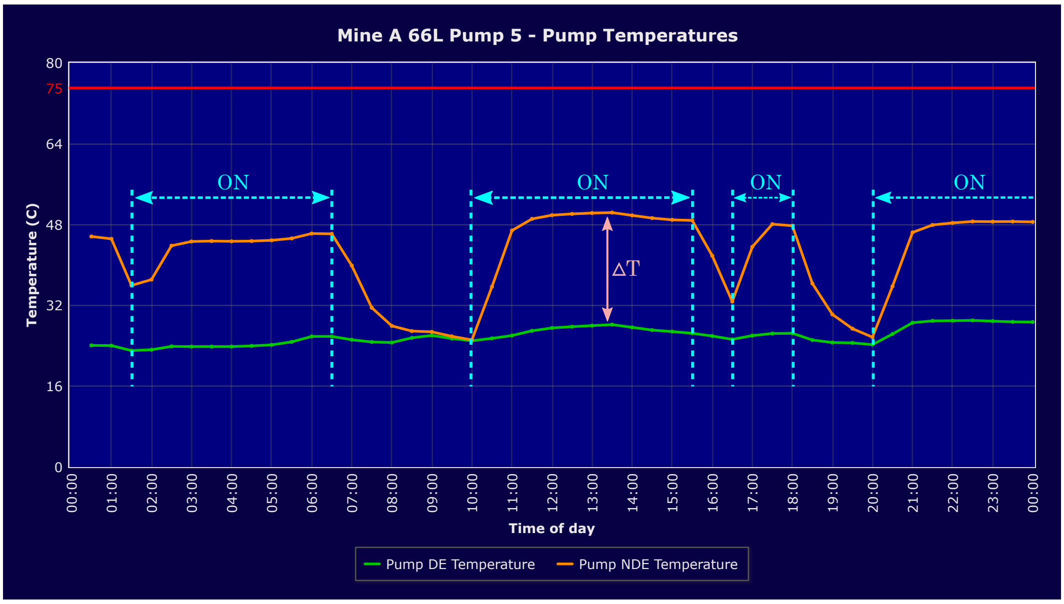


Figure 6.23: *Mine A - Initial parameter profile of faulty temperature measurement*

An investigation was performed to determine the root cause of the incorrect measurements. In this case it was found that the instrumentation was disconnected. The problem was therefore readily solved. Figure 6.24 shows the corrected temperature reading. It can now be observed that the two temperatures followed the same pattern. The temperature difference (ΔT) has also been decreased to an acceptable margin.

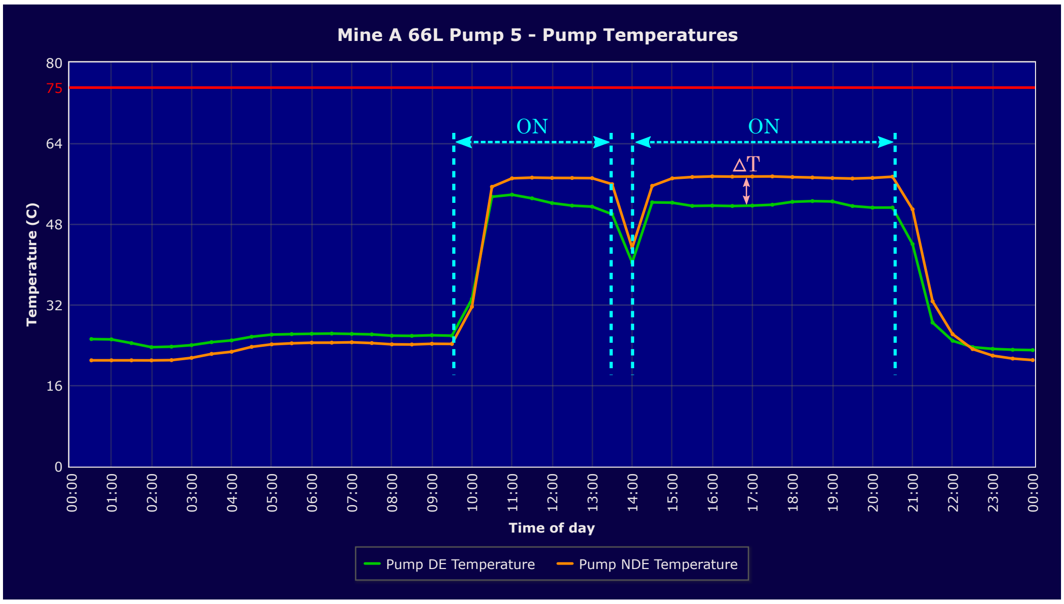


Figure 6.24: *Mine A - Daily profile of temperature measurements following repair work*

In some other cases of incorrect readings, it was found that water had mixed with the oil, which affected the temperature reading. In these cases, mechanical fitters were given a work order to prevent this from happening.

Assessment overview

The previous sections have illustrated how the automated system has identified operational risks and provided the user with summarised information regarding these risks. Some parameter evaluations were selected to validate the risk identification process. The risk parameters that were used in the illustrations do, however, represent a small portion of the total number of input parameters.

The daily risk identification process consisted of 218 parameters. Considering the raw data (two-minute samples), it equates to 156 960 daily data points and 4.7 million monthly data points. The raw data was however aggregated to half-hourly averages (48 values per parameter per day). The analysed data therefore amounts to 10 464 daily data points. Figure 6.25 illustrates how the total data points that were analysed over a 30-day period, for all four mining systems exceeded 300 000. Due to the scalable design of the system, the user can configure additional parameters to be analysed.

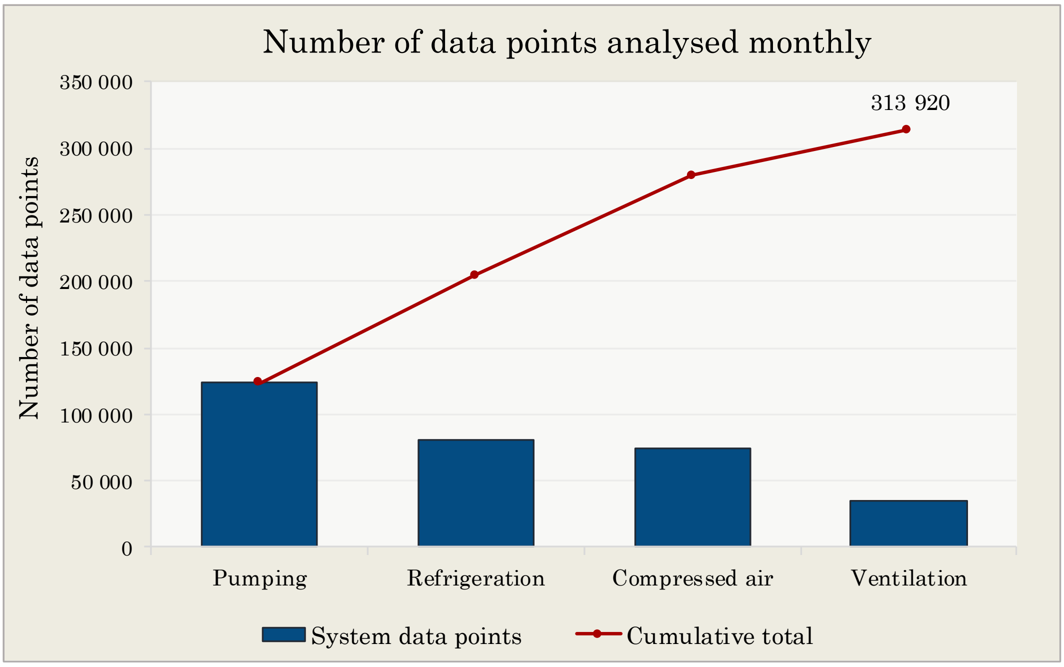


Figure 6.25: *Mine A – Monthly data points*

The exception report and system-specific reports summarise the results from the risk analyses. Only the parameters in the medium- and high-risk category are included in the reports.

Figure 6.26 displays the number of risk parameters (critical or warning) that were identified, for each of the four mining systems over a 30-day period.

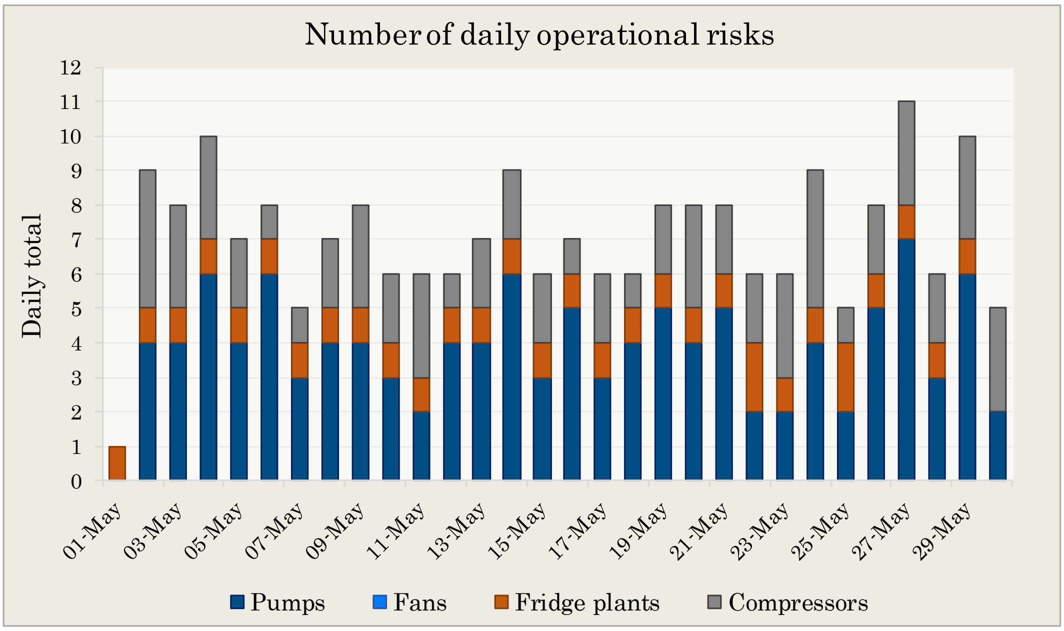


Figure 6.26: *Mine A – Daily number of operational risks*

The number of risks that were identified during this period were used to produce the distribution chart shown in Figure 6.27. The chart indicates that between six and ten parameters were identified as possible risks for 25 out of the 30 days. Thus, the user would only need to evaluate 5% of the input parameters on a typical day.

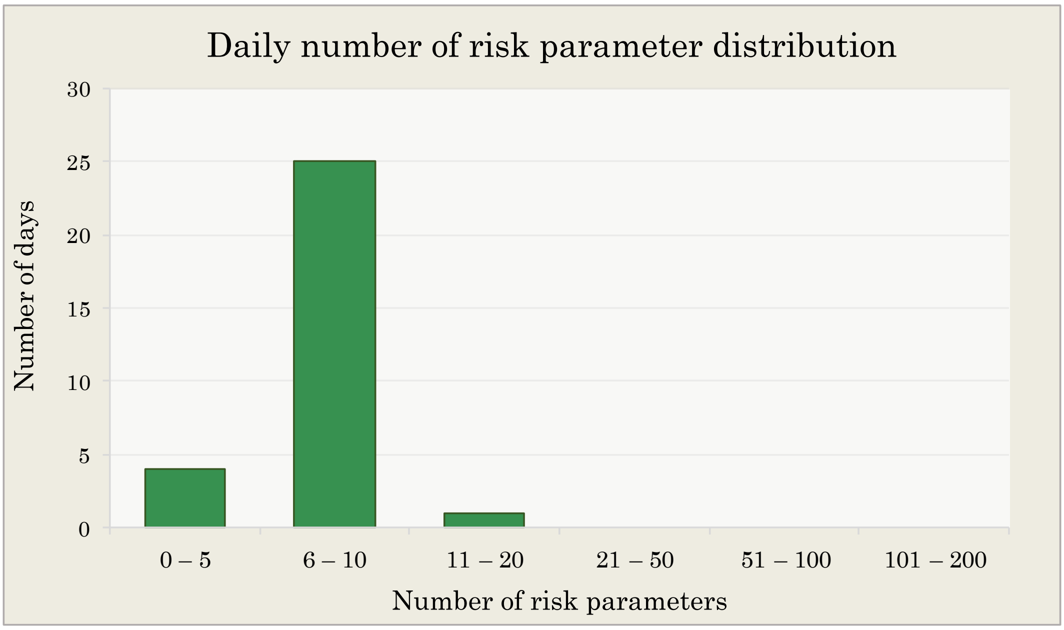


Figure 6.27: *Mine A – Number of risk parameter distribution*

6.4 Case study 2: Mine B

Mine B forms part of the mining group's northern operations. Table 6.3 lists the site specifications.

Table 6.3: *Mine B – Site specifications*

Specification	Mine B
Mine location	South Africa
Maximum mining depth	> 3 km below surface
Cash operating cost (R/kg)	> 400 000

Implementation details

Figure 6.28 shows an overview of the implementation. The illustration indicates the number of subsystems and the corresponding number of input tags that were used for each of the four main systems. 146 alarms were configured to send SMS alerts to six mine employees. A total of 495 input values were received and translated every 30 minutes. 264 online formatting tags were updated daily to indicate where risks have been identified. 150 exception reports were compiled and 480 emails were delivered over a 30-day period.

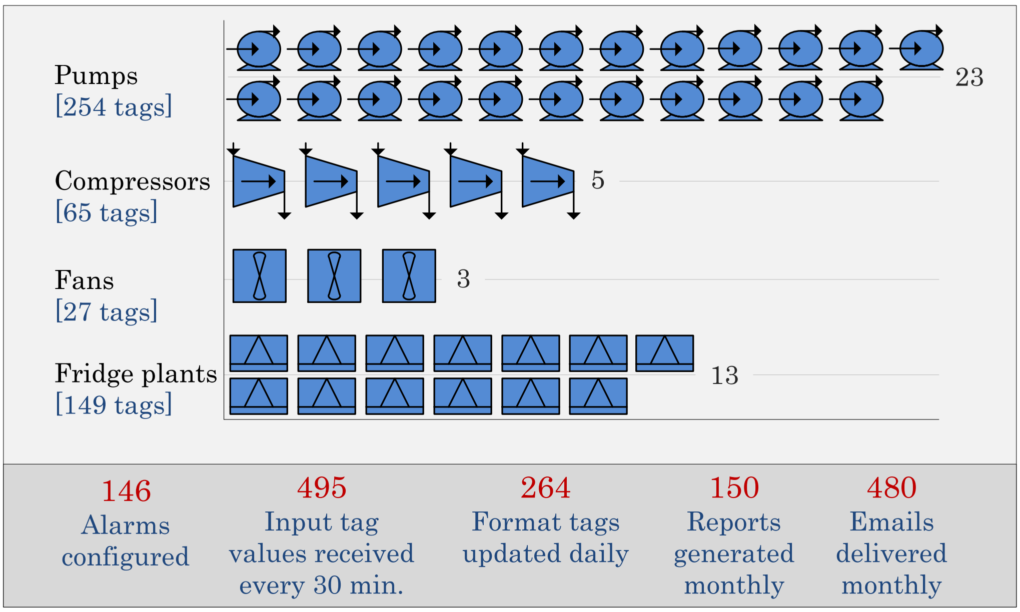


Figure 6.28: *Mine B – Overview of implementation*

Table 6.4 lists the input parameters that were evaluated daily. Certain parameters were not available for all of the subsystems.

Table 6.4: *Mine B – Input tag parameters*

Pumps	Compressors	Fans	Fridge Plants
Motor vibration	Motor DE vibration	Motor DE vibration	Motor DE vibration
Pump vibration	Motor NDE vibration	Fan DE vibration	Motor NDE vibration
Motor DE[1] temperature	Compressor DE vibration	Fan NDE vibration	Compressor DE vibration
Motor NDE[2] temperature	Compressor NDE vibration	Motor DE temperature	Compressor NDE vibration
Pump DE temperature	Gearbox vibration	Motor NDE temperature	Motor DE temperature
Pump NDE temperature	Motor DE temperature	Fan DE temperature	Motor NDE temperature
Motor power	Motor NDE temperature	Fan NDE temperature	Compressor DE temperature
Suction pressure	Compressor DE temperature	Motor current	Compressor NDE temperature
Discharge pressure	Compressor NDE temperature	Motor power	Evaporator temperature in
	Gearbox DE temperature		Evaporator temperature out
	Gearbox NDE temperature		Condenser temperature in
	Gearbox Thrust DE temperature		Condenser temperature out
	Gearbox Thrust NDE temperature		Evaporator flow
			Condenser flow

[1]Drive end (DE)
[2]Non-drive end (NDE)

The following figures show the various dashboards of Mine B. Each figure shows the current state of the system to illustrate the system implementations for an arbitrary day.

Figure 6.29 shows the compressed air dashboard of Mine B. The system comprises five compressors with rated capacities ranging from 1 MW to 3 MW.

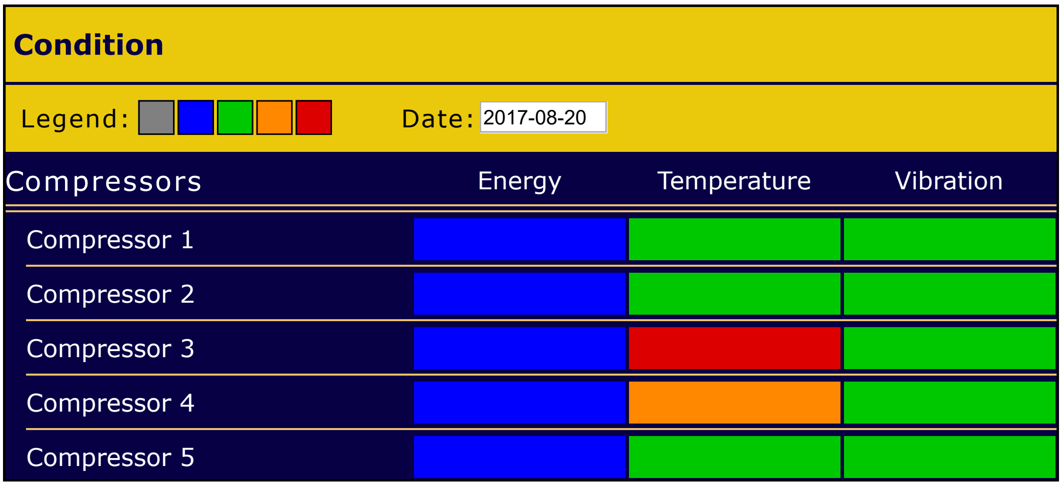


Figure 6.29: *Mine B – Overview dashboard of the compressed air system*

Figure 6.30 shows the refrigeration dashboard of Mine B. Four refrigeration plants are located on the surface, while nine plants are located on two separate underground levels.

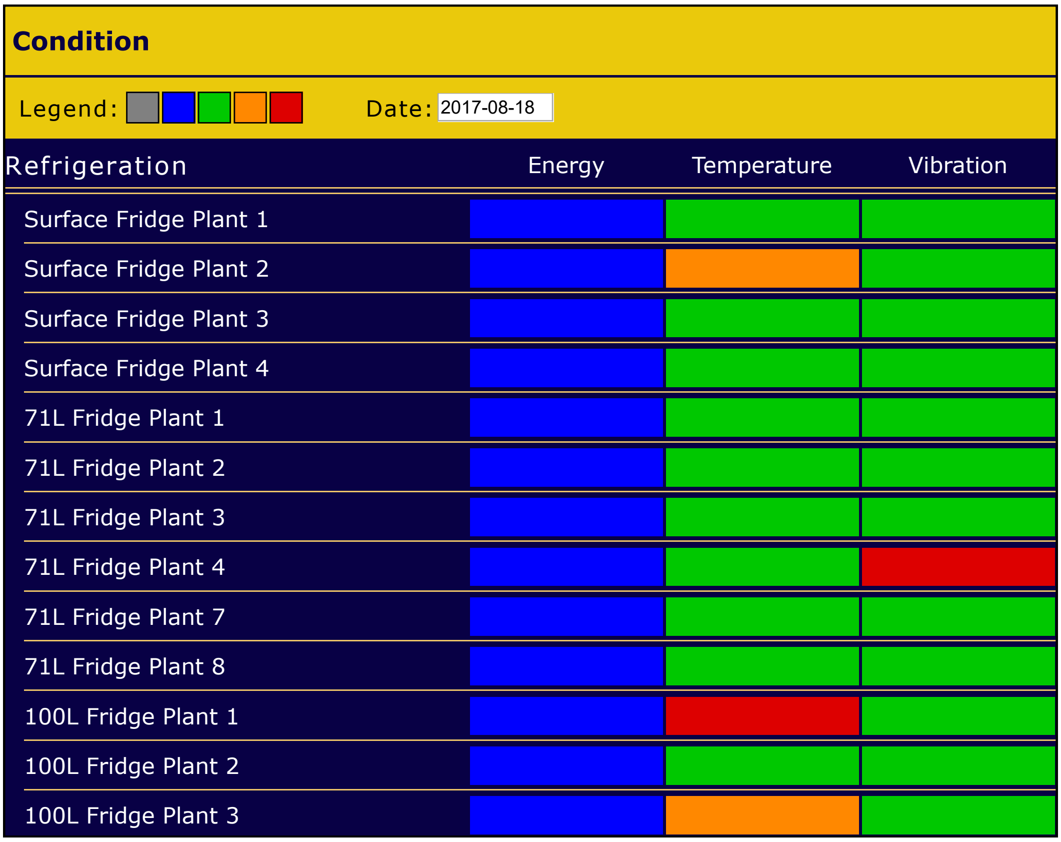


Figure 6.30: *Mine B – Overview dashboard of the cooling system*

Figure 6.31 shows the ventilation dashboard of Mine B. The three fans are located on the surface of the mine.

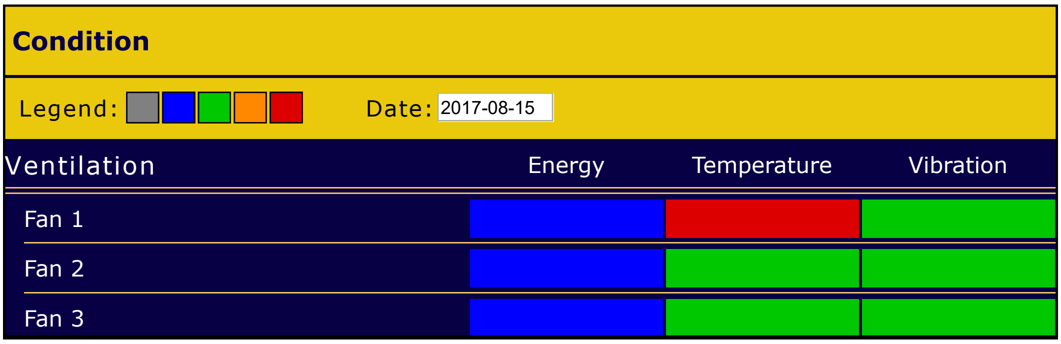


Figure 6.31: *Mine B – Overview dashboard of the ventilation system*

Figure 6.32 shows the water reticulation dashboard of Mine B. The system consists of 25 dewatering pumps, located on five mining levels.

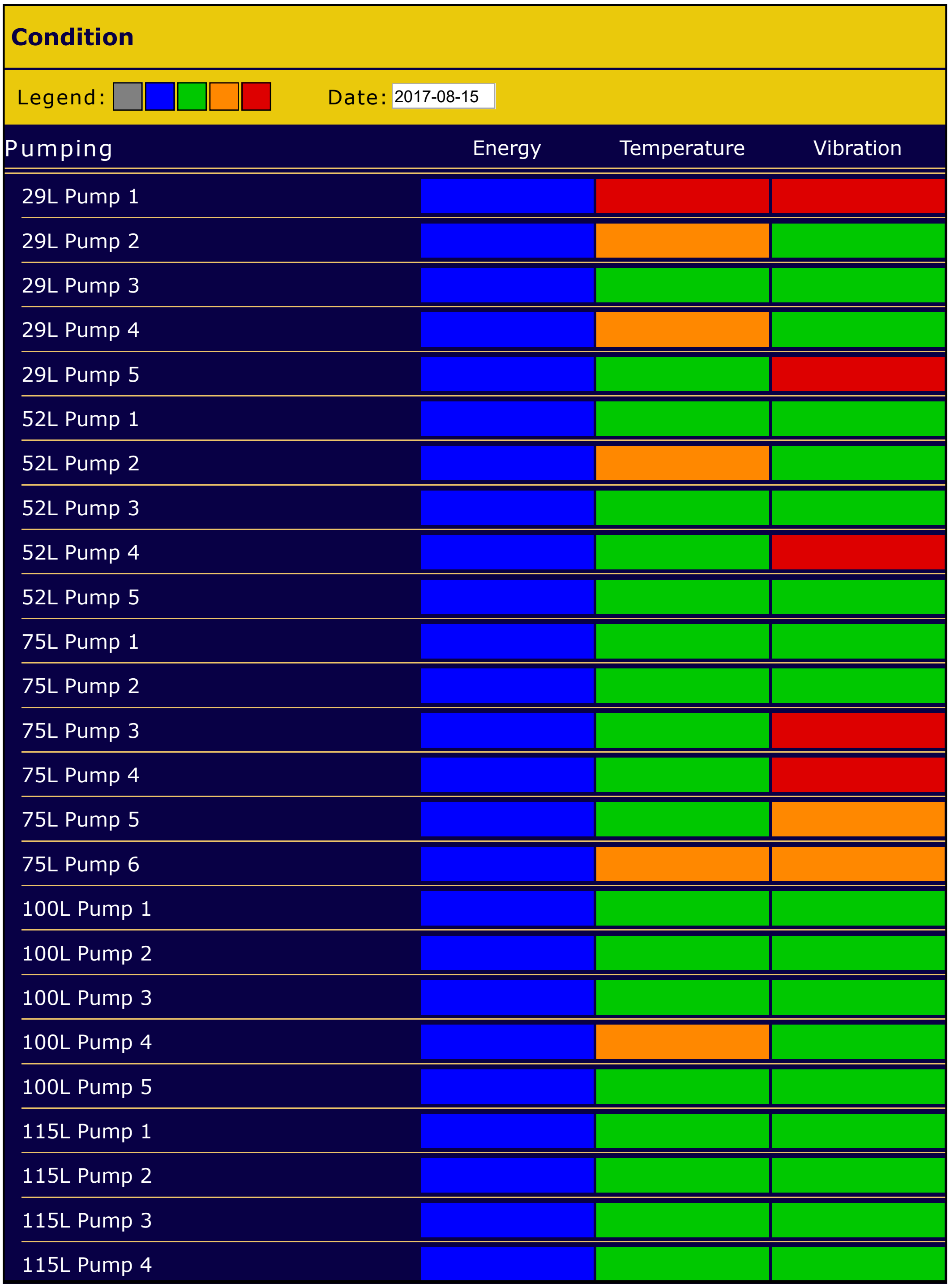


Figure 6.32: *Mine B – Overview dashboard of the water reticulation system*

Assessment results

Numerous operational risks were identified on Mine B. Several dewatering pumps operated at excessive vibration levels. This case study's discussions will, however, focus on the three remaining mining systems to illustrate the multiple system analysis capability. Due to the size of the operation, the exception reports and online platform were found to be invaluable to monitor the current state of the respective mining systems.

Operational risk identification

The site personnel were informed of possible risks according to the notification strategy that was developed for Mine B. These notifications were sent to the senior site engineers, as well as the group asset and maintenance managers.

This section's content was selected in a such a way for it to be considered as thorough without extending beyond sufficient validation. The exception report and system-specific reports will therefore only be used to illustrate the refrigeration system's risk identification process. The risks related to the compressed air and ventilation systems will be demonstrated with the relevant risk profiles.

The first operational risk that will be discussed occurred on an underground refrigeration plant. 100L Fridge plant 1 (100L FP1) had been exhibiting high temperatures on the motor DE bearings for a period of time. At one stage, a significant change was observed in the motor vibration risk scores. Figure 6.33 shows the exception report indicating that both the motor temperature and vibration have exceeded their respective critical limits.

Summary of critical exceptions

Parameter	Critical Limit	Violation duration (hours)	Violation period average
100L FP1 Motor DE Temperature	80.0°C	24	82.0°C
100L FP1 Motor DE Vibration	4.0 mm/s	24	4.4 mm/s
100L FP1 Motor NDE Vibration	4.0 mm/s	17.5	4.2 mm/s
Comp3 Gbox Pin NDE Temperature	65.0°C	24	68.6°C
52L P4 Motor Vibration	4.5 mm/s	14	5.2 mm/s
75L P6 Motor NDE Temperature	75.0°C	12.5	75.8°C
29L P1 Pump Vibration	4.5 mm/s	9	5.8 mm/s
29L P5 Pump Vibration	4.5 mm/s	9	9.8 mm/s
75L P3 Pump Vibration	4.0 mm/s	3	4.1 mm/s

Figure 6.33: *Mine B – Example of an exception report*

The refrigeration report also indicated that 100L FP1 had been operating in the risk- and failure regions. The risk- and failure region totals can be seen in Figure 6.34.

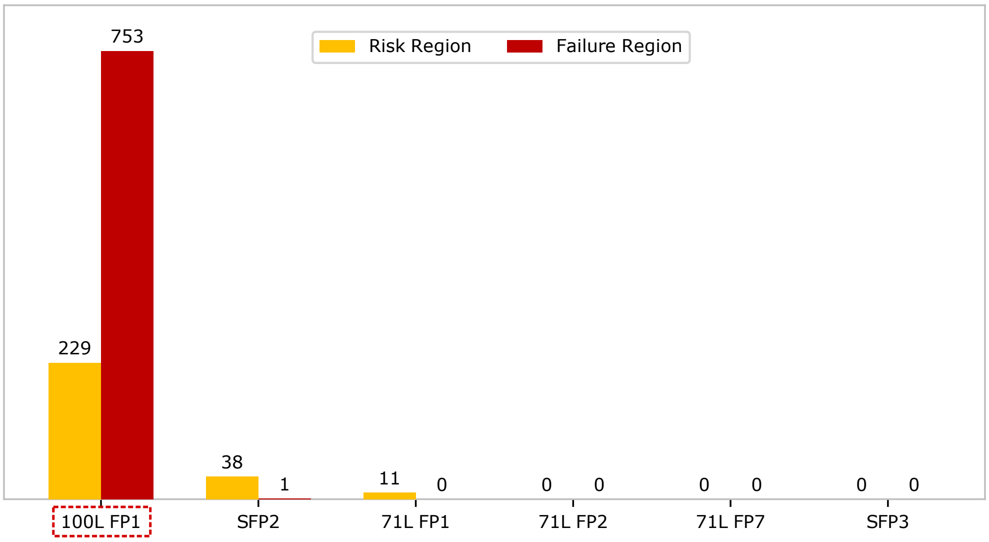


Figure 6.34: *Mine B – Refrigeration plant risk and failure region totals*

The parameter distribution graphs provide more detail regarding the risk- and failure region totals. The motor temperature and vibration parameters, listed in the exception report, were the main contributors towards the failure region total. Only the vibration parameters are discussed in more detail in order to demonstrate the identification of a sudden operational change. Figure 6.35 shows the failure region totals for the vibration parameters.

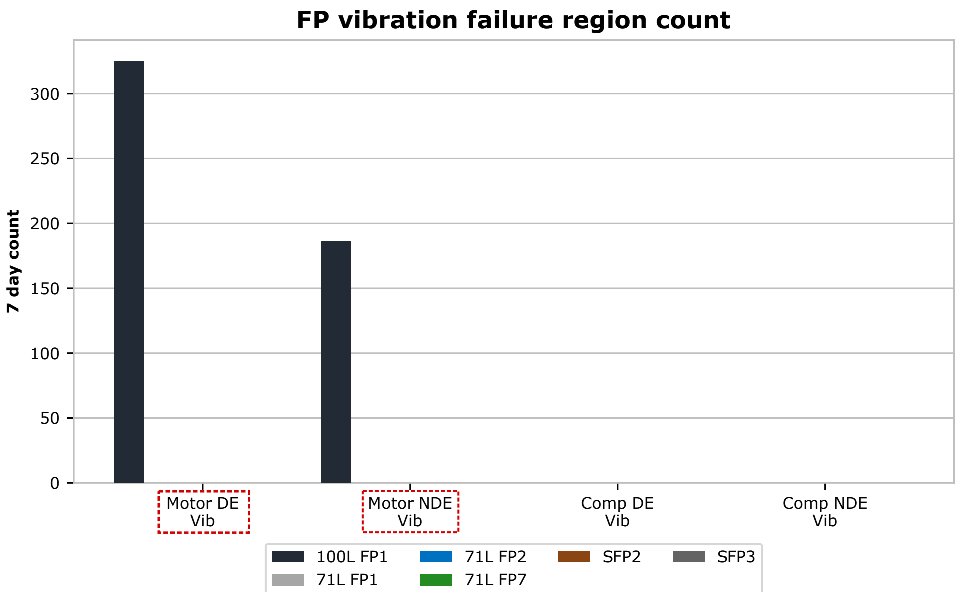


Figure 6.35: *Mine B – Failure region totals of vibration parameters*

It is evident from the risk score profile (Figure 6.36) that the motor DE vibration moved from the low-risk region into the high-risk region over a short period of time.

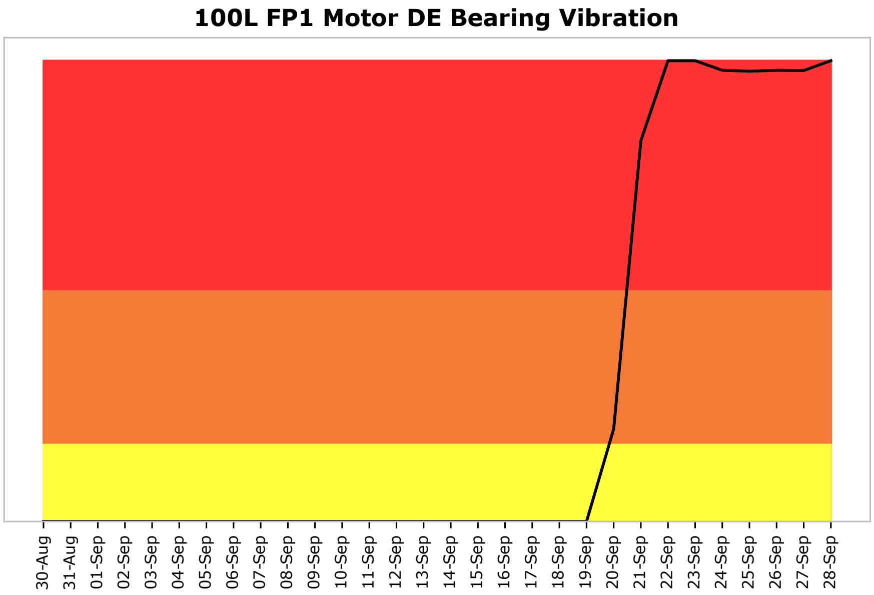


Figure 6.36: *Mine B – Risk score profile of the motor DE vibration*

The corresponding SCRF profile, shown in Figure 6.37, indicates that the region of operation shifted from the Safe region to the Failure region.

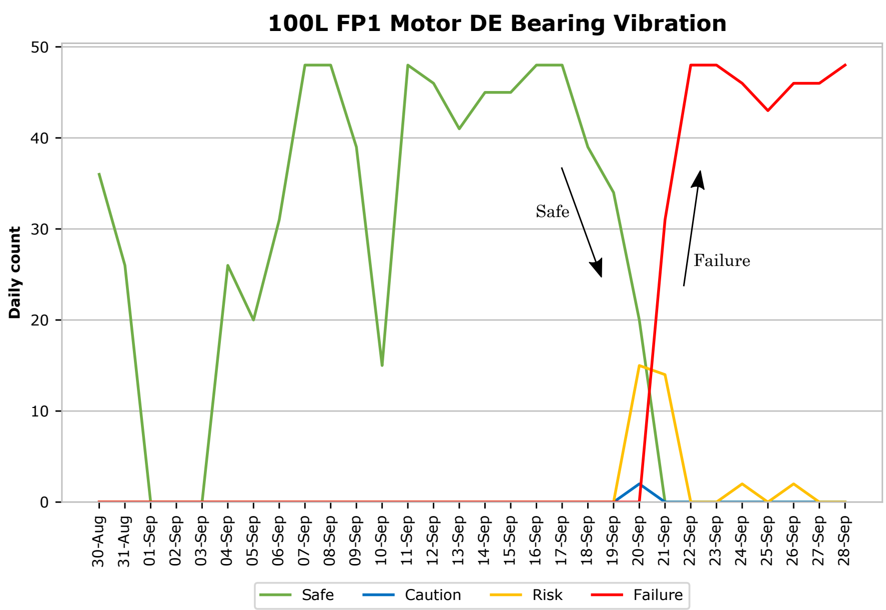


Figure 6.37: *Mine B – SCRF profile of the motor DE vibration*

The risk evaluation of the motor NDE vibration (Figure 6.38) also displayed a sudden change from low- to high-risk.

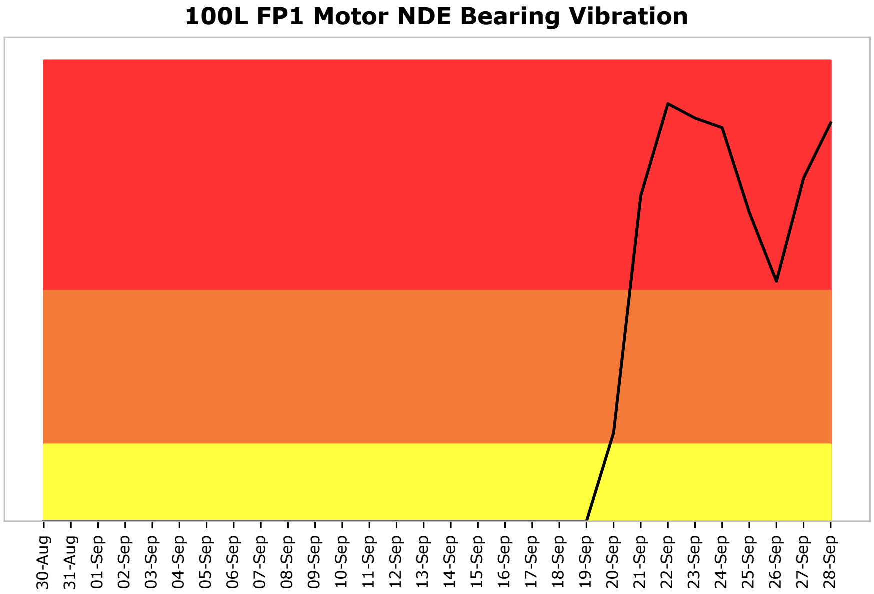


Figure 6.38: *Mine B – Risk score profile of the motor NDE vibration*

Figure 6.39 shows the corresponding SCRF profile, which indicates that the motor NDE vibration ceased to operate in the Safe region. The vibration measurements subsequently moved into the Risk and Failure regions.

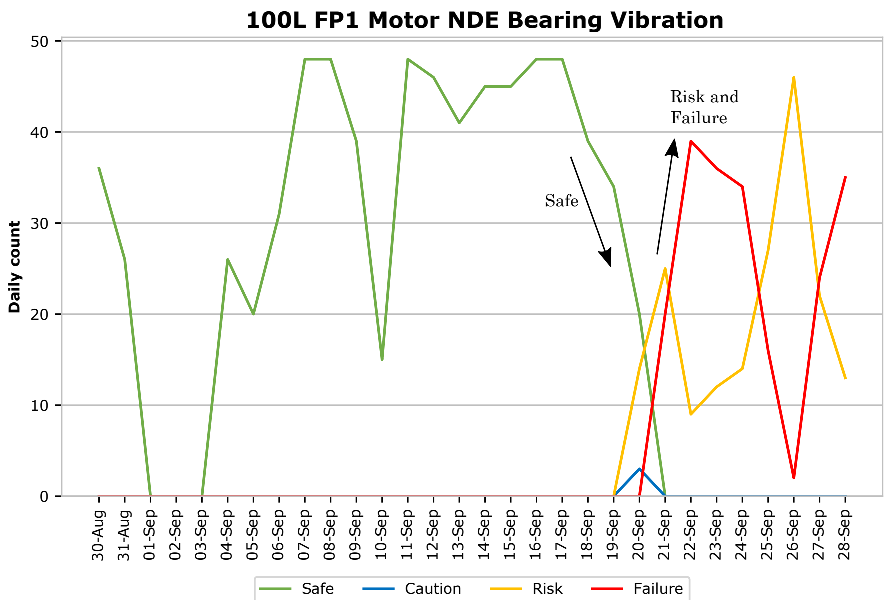


Figure 6.39: *Mine B – SCRF profile of the motor NDE vibration*

Operational risks were also identified on the compressed air system. One of these risks was selected to be discussed here. Figure 6.40 demonstrates how the gearbox thrust temperature, associated with Compressor 4, gradually progressed from the low- to the high-risk region.

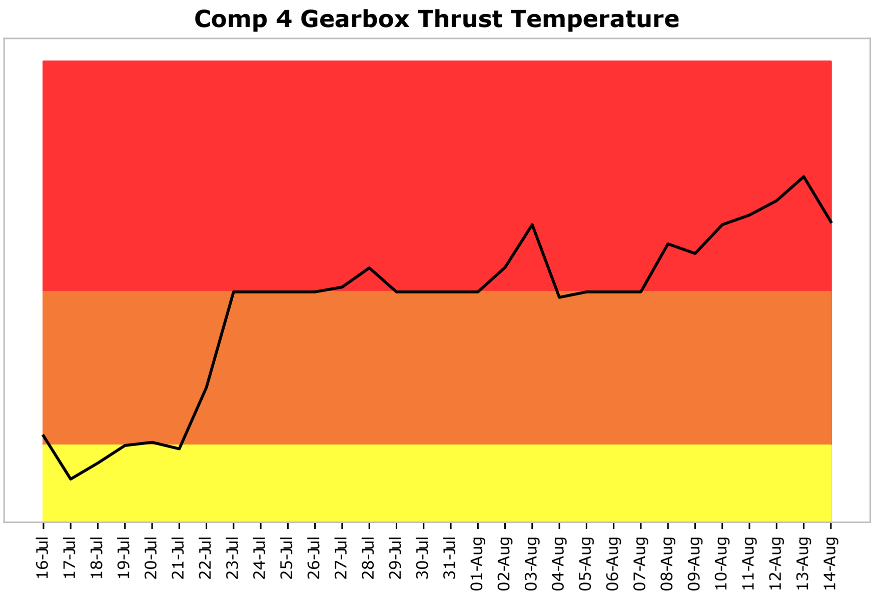


Figure 6.40: *Mine B – Risk score profile of the gearbox thrust temperature*

It can be observed from the SCRF profile (Figure 6.41) that the temperature parameter initially moved from the Safe and Caution regions to the Risk region. After a period of two weeks, the gearbox temperature progressed into the Failure region.

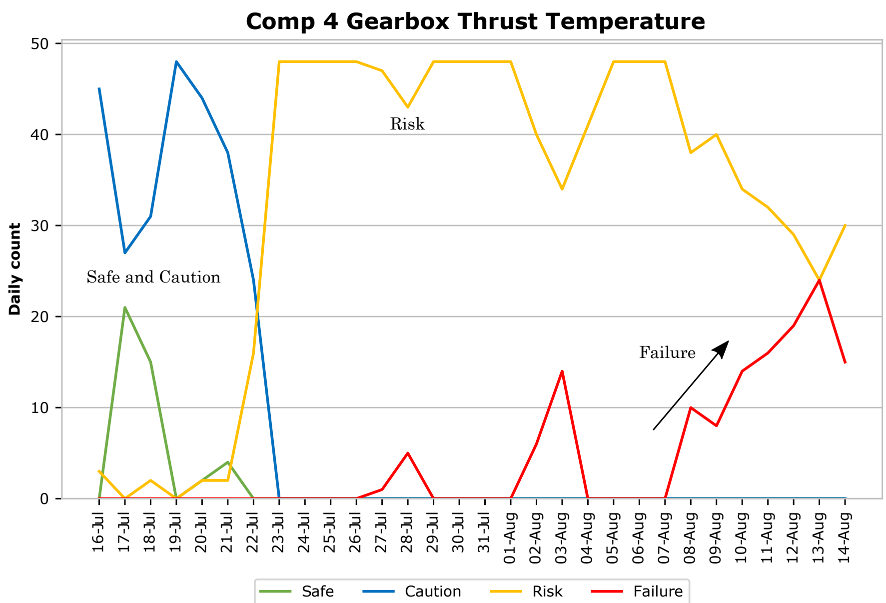


Figure 6.41: *Mine B – SCRF profile of the gearbox thrust temperature*

Figure 6.42 illustrates how a temperature risk was detected on one of the ventilation fans on Mine B. The risk category of the fan DE temperature changed from low to medium. It subsequently deteriorated from medium to high, and remained high.

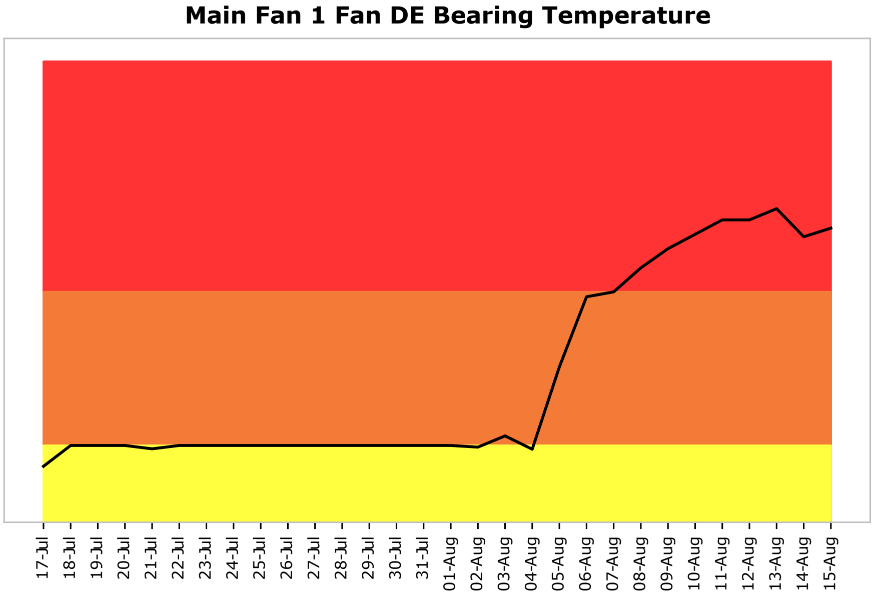


Figure 6.42: *Mine B – Risk score profile of the fan DE temperature*

The region of operation initially changed from Safe to Caution. After some time, the fan temperature exceeded the Caution region's boundary and moved into the Risk region. Shortly after that, the fan temperature operated within the Failure region.

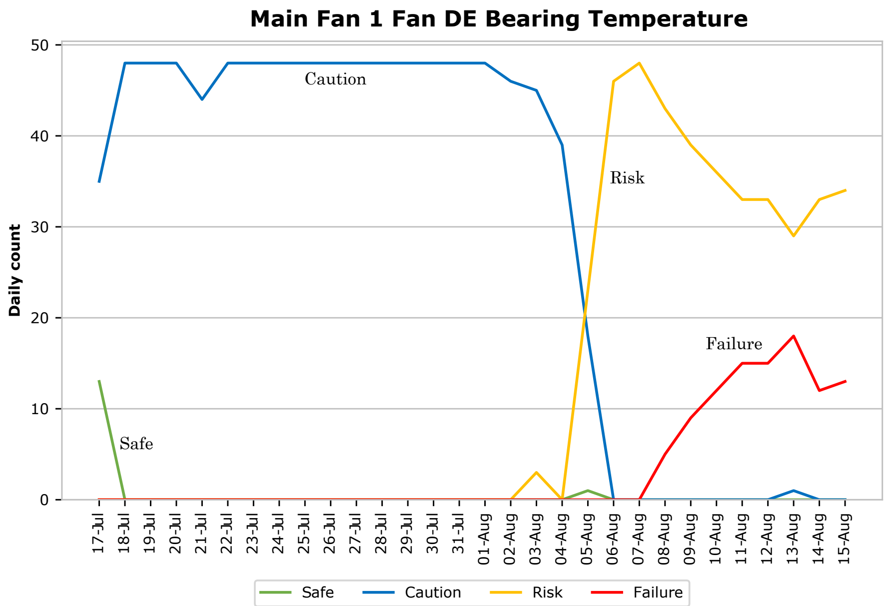


Figure 6.43: *Mine B – SCRF profile of the fan DE temperature*

Risk validation and remedial action

The following parameter profiles validate the operational risks that were identified. These profiles were obtained from the online platform and show the actual input signals for the time periods during which the operational changes were identified. Although the mine personnel were notified of these risks, the corrective maintenance could not be performed in time for the post-implementation results to be shown here.

Figure 6.44 displays the vibration profiles that correspond with the risk analyses shown in Figures 6.36 and 6.38. The risk analyses for the motor DE and motor NDE vibrations indicated that a sudden operational change occurred. The vibration graph confirms that both the motor vibrations increased from about 1 mm/s, to more than 4 mm/s. Considering that the alarm limit was 4 mm/s, it is evident that the motor operated within the failure region. The risk was therefore identified before the vibrations reached the trip limit of 6 mm/s.

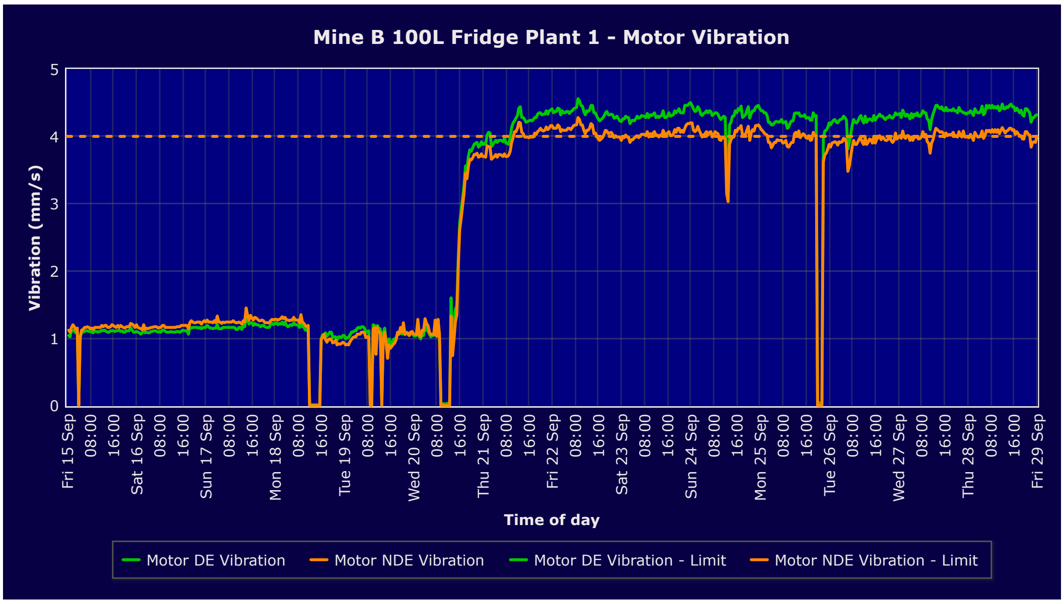


Figure 6.44: *Mine B – Profile of the motor vibration exceeding the alarm limit*

The next parameter that was discussed in the risk identification section is the gearbox thrust temperature associated with Compressor 4. Figure 6.40 indicated that the gearbox temperature exceeded the safe operating limits. Figure 6.45 shows the temperature profile for the period during which it began to approach the failure region. During this period, the temperature increased from 55°C to the critical limit of 60°C. Thereafter, it continuously exceeded the critical limit. A gradual increase in temperature was therefore detected by the system analysis.

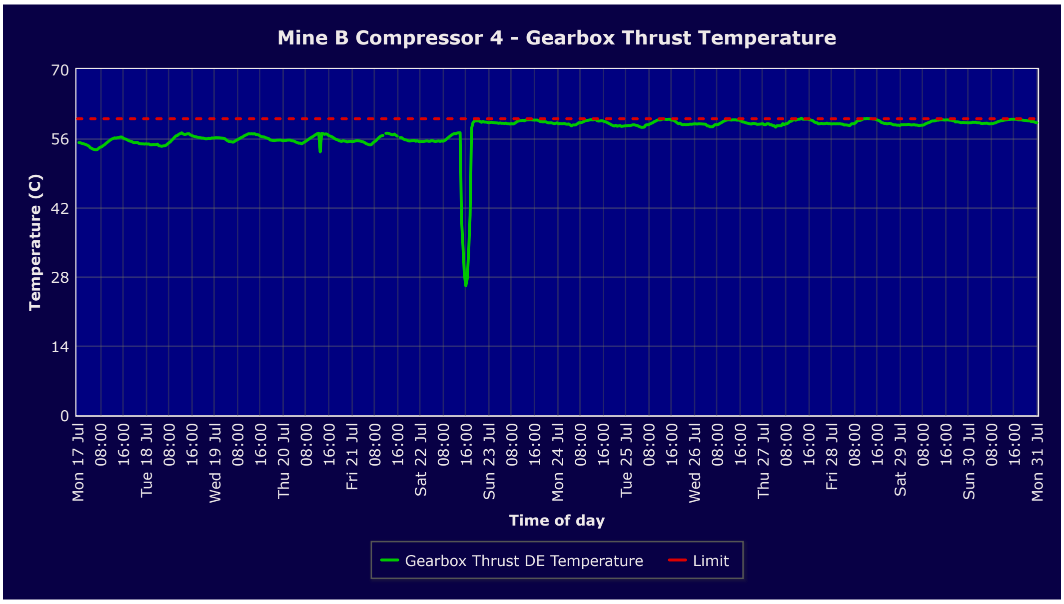


Figure 6.45: *Mine B – Profile of the gearbox temperature exceeding the alarm limit*

The final risk evaluation that was presented (Figure 6.42) was the fan DE temperature associated with Ventilation Fan 1. Figure 6.46 shows the temperature profile that corresponds with the risk evaluation period. Considering the DE temperature, an increase from 68°C to its critical limit of 75°C can be observed. The risk assessment was therefore accurate. This example demonstrated the detection of a subtle temperature increase that may have been overlooked.

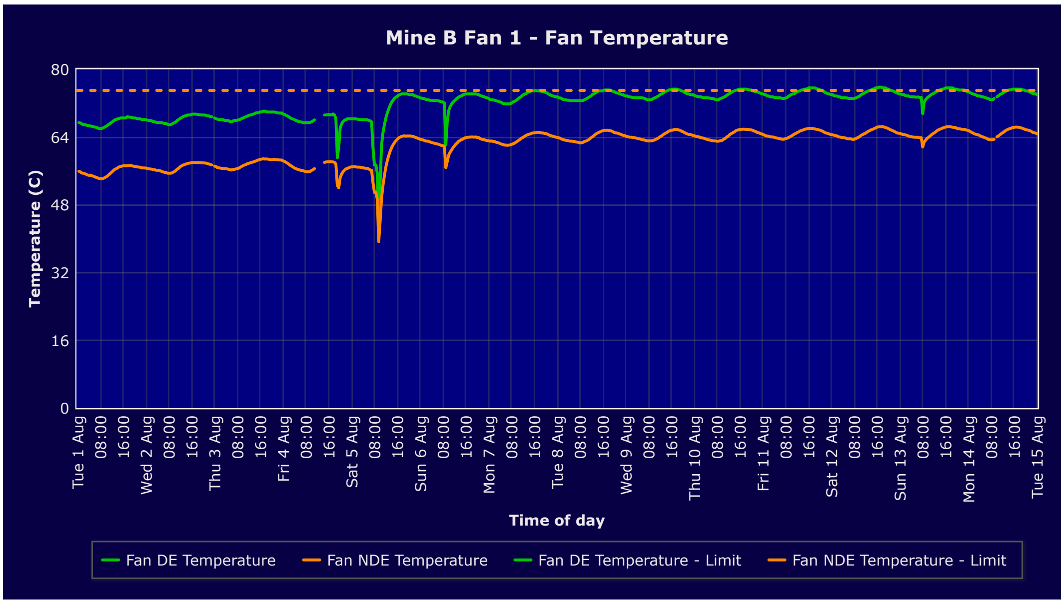


Figure 6.46: *Mine B – Profile of the fan temperature exceeding the alarm limit*

Assessment overview

The second case study has proven that the information system is scalable. Although the configuration sheets of Mine B contained more entries than Mine A, the system analysis and deliverables remained the same. The system configuration of Mine B took one week to complete. Here the system configuration refers to the local server setup once the input tags were available.

The daily risk-identification process consisted of 495 input parameters. Considering the raw data (two-minute samples), it equates to 356 400 daily data points and 10.6 million monthly data points. The raw data was, however, aggregated to half-hourly averages (48 values per parameter per day). The data analysis therefore consisted of 23 760 daily data points. Figure 6.47 illustrates how the total data points that were analysed over a 30-day period exceeded 700 000 for all four mining systems.

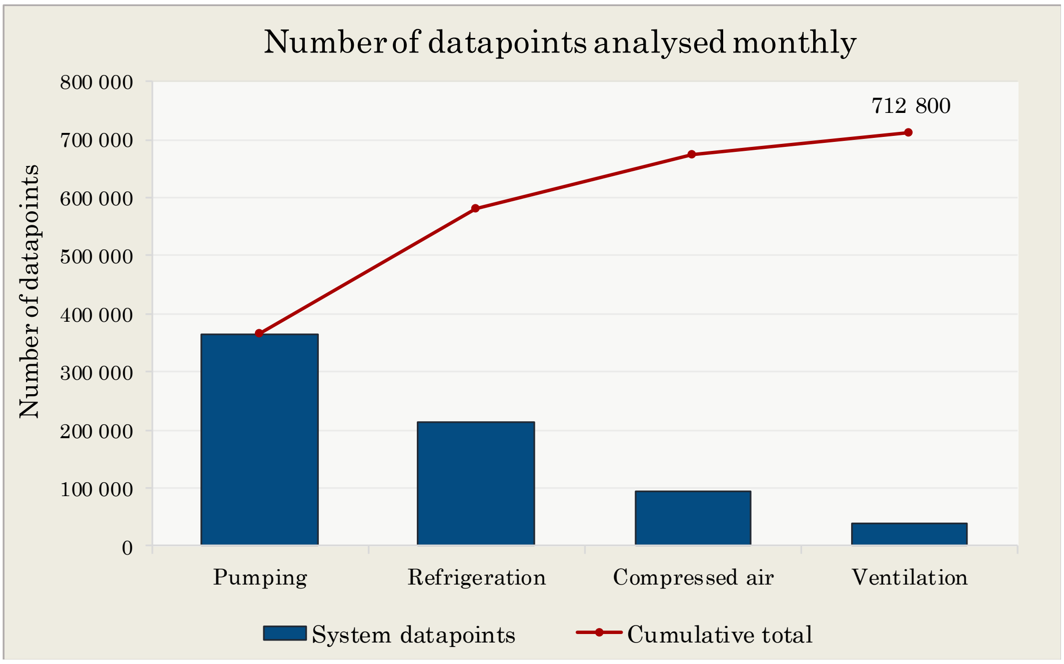


Figure 6.47: *Mine B – Monthly data points*

Exception reports were used to only convey the necessary information to the user. This was achieved by compiling these reports dynamically every day. A risk score condition was used to only include parameters which are in the medium- or high-risk category. Figure 6.48 displays the number of risk parameters (critical or warning) that were identified for each of the four mining systems over a 30 day period.

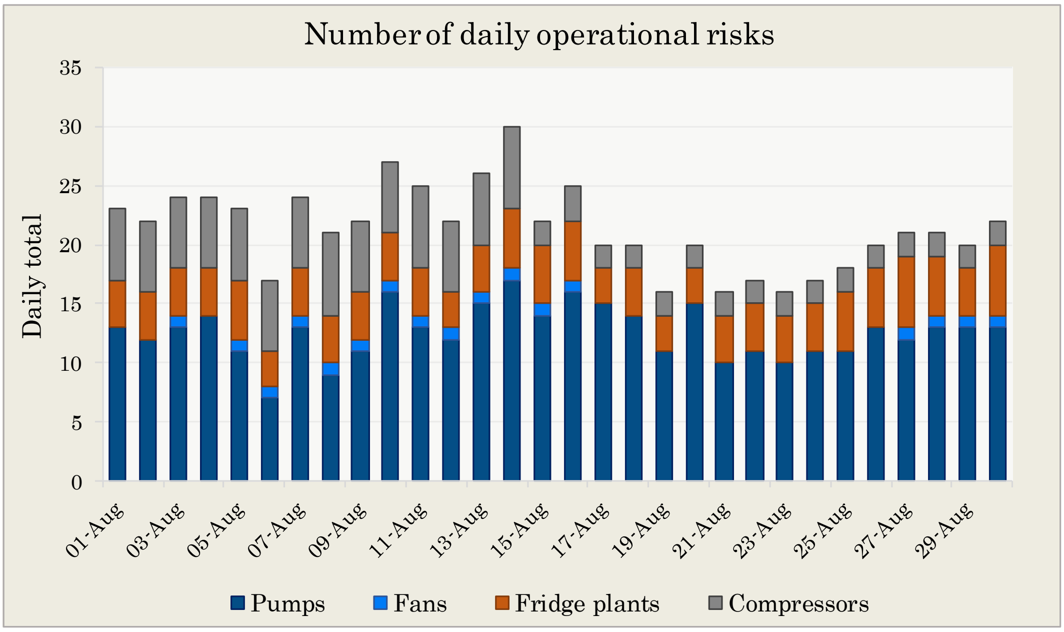


Figure 6.48: *Mine B – Daily number of operational risks*

The risk information from this period was used to produce the distribution chart shown in Figure 6.49. From the chart it is evident that on most of the days, between 21 and 30 parameters were identified as possible risks. Thus, on average, the user would need to evaluate less than 6% of the input parameters.

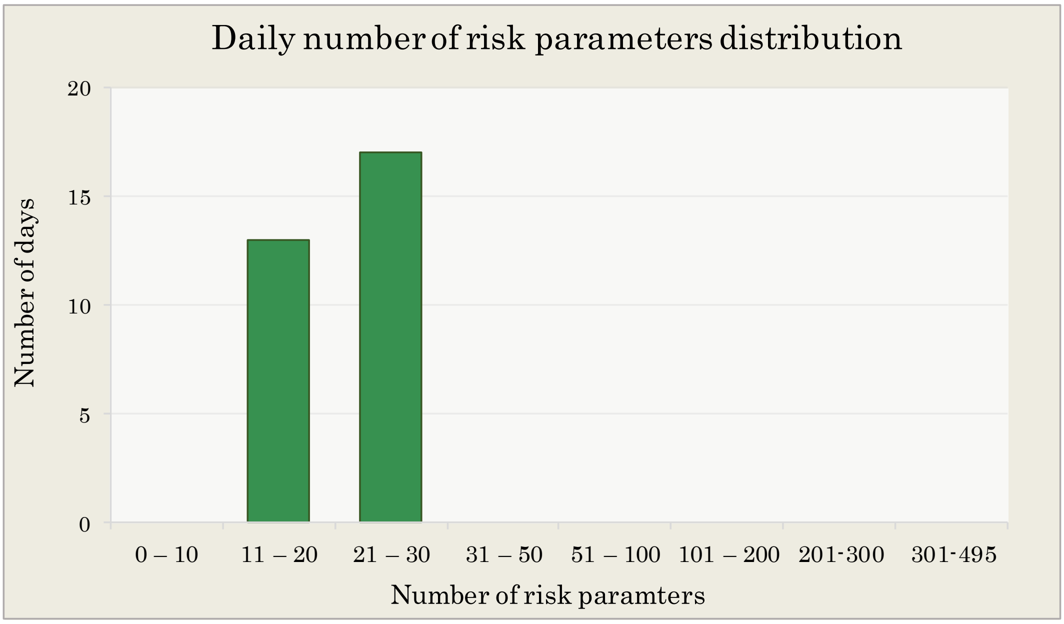


Figure 6.49: *Mine B – Number of risk parameter distribution*

6.5 Implementation review

The information system was implemented on six deep level mines affiliated with the same mining group. Two mines were selected to be presented as case studies for the system validation. These two mines form part of the North and South operations respectively. The information system therefore made it possible to monitor mining operations that are 230 km apart.

The mining group incorporated the system notifications into their maintenance strategy. Work orders were generated according to the results that were obtained from the risk analyses. The information system was instrumental in the development of the mining group's *Line-of-sight* approach. This approach formed part of their system awareness campaign.

It was through this newly created awareness and early fault detection that the mine was able to improve the condition of their machinery. Case study 1 has shown that corrective maintenance can restore equipment to a healthy state. Figure 6.50 demonstrates how the critical notifications on Mine A have decreased since commissioning of the information system. 61 exception parameters were identified during the first month. This number was reduced to 25 during the second month, primarily resulting from minor maintenance interventions and more accurate region definitions. During the following four months, the number was reduced further to an average of nine exceptions per month. This can be attributed to regular system examinations and overhauls.

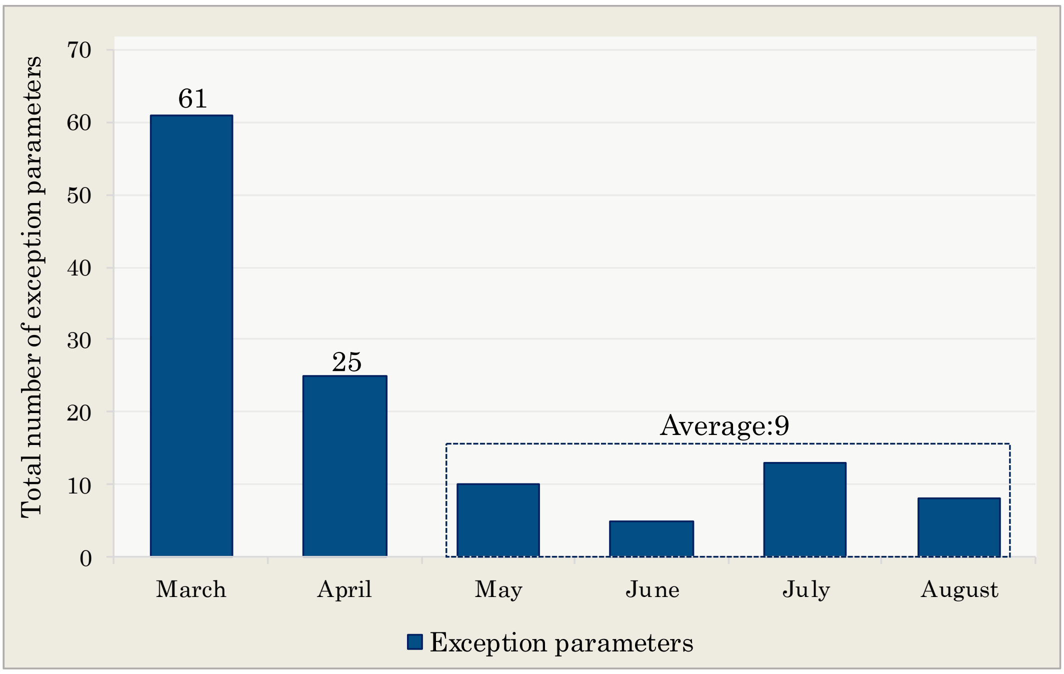


Figure 6.50: *Monthly critical exceptions on Mine A*

6.6 Summary

Six mining operations, which form part of the same mining group, were selected for the system implementation. The condition of various mining systems was evaluated on a continuous basis. Operational risks, or system exceptions, were generated by each individual system analysis. These system exceptions were also combined to provide a holistic site overview. The online availability of system information enabled the mining group executives to be aware of the issues on each site. The centralisation of information was therefore a valuable contribution towards the operational awareness on the mines.

Risk notifications were generated according to the relevant site's alarm limits. In addition to alarm limit violation detection, the data analyses indicated when input values were approaching these limits. The operational risks were automatically compiled in different formats, including SMS alerts, automated reports and an online interface, thus replacing a time-consuming and labour-intensive task. This enabled mine personnel to investigate the failure symptoms and schedule maintenance when deemed necessary. It was subsequently shown that operational risks can be reduced by performing CBM.

CHAPTER 7

Conclusion

7.1 Summary of work done

The limited accessibility and harsh environment of deep level mines make the monitoring of equipment a challenging task. The lack of continuous condition monitoring results in equipment deterioration going unnoticed. Failure symptoms, or signs of possible malfunction, indicate that maintenance is needed. Literature has shown that neglecting to service or repair these operating modules can result in major repairs or part replacements that require longer downtime and accumulate higher costs. The work that was done therefore aimed to make CBM possible in a mining environment.

An integrated information system was designed and developed for deep mines. The system was used to monitor the operational condition of mining equipment and was implemented on six South African mining sites. An overview of the implementation is given in Figure 7.1.

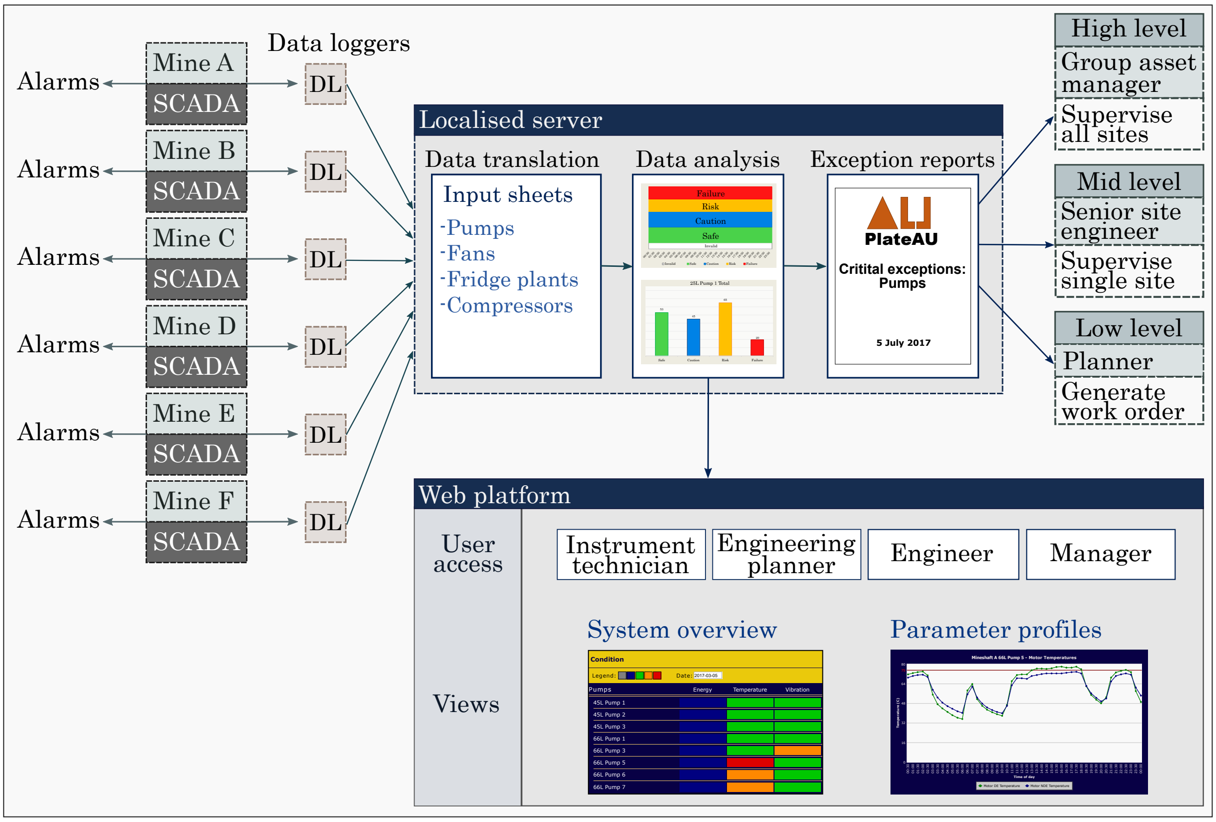


Figure 7.1: *System implementation overview*

Servers on site were used to configure alarms and log the relevant data. Alarms were configured on each site to notify site-specific personnel, in real time, of parameters exceeding their alarm limits. Alarm notifications were sent via email or SMS. Data loggers were used to log the required input data from the SCADA via an OPC connection, aggregate the values to half-hourly averages and generate log files automatically. An existing mail application was configured to email the log files every 30 minutes.

Four major mining systems were evaluated. These four systems consist of water reticulation, compressed air, cooling and ventilation systems. Depending on the input tag availability, pumps, compressors, refrigeration plants and ventilation fans were assessed. The system design allows for multiple types of parameters to be analysed. Vibration and temperature inputs were selected for the initial proof of concept, due to their proven value as equipment health indicators.

Three modules were used to translate the incoming data into information. The functionality of an existing data translation system was leveraged to prepare the necessary input sheets. These sheets contain the input data of the selected tags for the selected date range.

An innovative *SCRF* methodology (Figure 4.2) was developed to evaluate the operational condition of equipment and present the results graphically. The method was designed to be used in an automated process. Python[1] was used for the software development of the calculation and reporting scripts, due to it being object oriented and open source (free to use). LaTeX[2] was chosen to typeset the reports, due to it being based on text commands and could therefore easily be incorporated into the Python code.

The SCRF methodology consists of four regions of operation that can be specified for each input parameter according to its operating limits. These regions are labelled *Safe*, *Caution*, *Risk* and *Failure*. Input signals are compared to the relevant region boundaries while the equipment is operational. A region total is subsequently calculated for each of the regions and displayed on a bar chart. The corresponding region totals of various parameters can be added together, thereby deriving a single result per subsystem.

In addition to the region totals, the methodology also calculates a risk score (Figure 4.10) for each parameter. A parameter's risk score is determined by using the region totals as weighted inputs. An adjustment is also made according to the running status count in order to identify possible risks, even if the equipment was only operated for a short period of time. Risk scores are subsequently divided into three categories, namely low, medium and high.

The analysis results are compiled in automated exception reports. The purpose of these reports is to only present the user with the necessary information. Exceptions in the current context can be defined as abnormal or unsafe operation. Parameters in the medium- or high-risk category were therefore added to the exception reports.

[1]Programming language – https://www.python.org/

[2]LaTeX Project Public License – https://www.latex-project.org//

Two types of reports were developed, namely a *site exception report* and a *system exception report*. The site exception report contains the operational risks of the previous day for all four systems. The system exception reports provide more detail regarding the identified risks on a specific system e.g. compressed air system. These reports contain a seven-day SCRF analysis, as well as 30-day risk profiles for the risk parameters.

The reports were sent to various stakeholders, from different levels within the mining group's corporate structure, on a daily basis. From a high-level perspective, the group asset manager received the site exception report for all six sites. From a mid-level perspective, the senior site engineering managers only received the relevant site exception. From a low-level perspective, the engineers and engineering planners received the system-specific exception reports. The distribution of relevant information therefore facilitated the operational awareness regarding equipment condition.

An online platform was used to display the results from the daily risk analyses. Format tags were used to colour the online health indicators green, orange or red, corresponding to risk categories of low, medium and high respectively. Separate health indicators were used for temperature and vibration to ease the user's identification of the risk parameters. The online platform also contains parameter profiles for all the input tags. These parameter profiles can be used to view historical data, as well as *live* tag data that is updated every 30 minutes. All the required personnel were given login credentials to access the applicable dashboards.

The information system automatically identified operational risks on mining equipment and generated risk notifications. Operational awareness regarding equipment condition was created and thereby promoted transparency within the corporate structure. The mine also integrated CBM with their existing maintenance strategy to reduce unnecessary costs and promote underground safety. The objectives that were identified in Section 1.5 were therefore achieved.

7.2 Key discussion points

The system implementation on six mining sites revealed some important findings. Although these mining operations look similar on paper (considering the equipment and environment), it was found that several differences exist in practice. A continuous improvement cycle was therefore followed during both the design- and implementation phases.

Available infrastructure was utilised as far as possible to lower the implementation costs. Input tag data was obtained from the mines' SCADA systems. No additional instrumentation was therefore installed. An existing data collection and translation system was re-purposed to accommodate the condition monitoring data.

The two case studies provided a comprehensive account of the implementation process. The time-consuming task of manually monitoring critical equipment was replaced by an automated risk identification process. Operational risks were successfully identified on several types of equipment. Input parameters were assessed on a daily basis, which enabled the identification of system defects before they developed into a serious condition.

Due to Case study 1 having a much earlier commissioning date, it was possible to document the operational improvements relating to the information system's risk identification. It was shown that equipment can be restored to a healthy condition by performing maintenance when it is needed. Incorrect temperature readings on an underground pump, due to a disconnected probe, was identified by the invalid data analysis (Figure 5.10) and was subsequently rectified.

The scope of Case study 2 was much larger than that of Case study 1, with twice as many subsystems and input parameters to be analysed. Considering that a new system configuration of this magnitude only took one week, the system design was validated to be configurable and scalable. The system configuration here refers to the setup on the local server once the input tags and corresponding alarm limits were available.

Alarm limits were initially configured as global limits, meaning that multiple subsystems (e.g. multiple pumps) were linked to the same limit. This strategy resulted in some parameters triggering an alarm too often (limit too low), while other parameter values increased without being noticed (limit too high). It was therefore decided to use component-specific limits. Alarm limits were configured according to a selected margin below the relevant trip limit.

The mining group incorporated the information system's notifications into their maintenance strategy. It was decided to integrate CBM with their existing schedule-based maintenance model. Although the information system is not considered to be a fully developed CBM system, it made personnel aware of operational risks and enabled them to perform maintenance when it was needed. The system therefore made a contribution towards the development of CBM for underground mines.

More than one million data points were analysed per month between the two sites that were discussed in the case studies. Although the hardware and software infrastructures made it possible to perform a data analysis, the SCRF methodology made it possible to translate large amounts of data into simplified information. The SCRF methodology can be implemented independently from the information system that was developed. A similar analysis procedure can be followed to characterise other types of input signals.

7.3 Future development

Throughout the thesis it has been made clear that opportunities exist for future development. Although only two parameter types were analysed in the case studies, the system design makes it possible to expand the configuration to include multiple types of parameters. Parameters such as balance flow, current and suction pressure can be added to obtain an improved operational health assessment.

Additional research can help to optimise the risk assessment for each individual mining system. A parameter-specific risk calculation can be developed to incorporate the relevant severity level. This would help identify components that require immediate attention when classified as being in the high-risk category.

Long-term use of the system may reveal additional insights regarding equipment failures on underground mines. Failure patterns can be better identified by using the system to monitor equipment deterioration. Supervisors might also be able to determine whether a failure was caused by worn-out components, or due to misuse.

Finally it is recommended to advance the study of CBM on deep level mines. It was found that there is a need for practically-feasible CBM solutions on deep mines. One suggestion would be to develop a strategy listing the requirements, implementation procedure and notification protocol of a CBM approach for underground mines. Future studies can also be performed to determine the total cost of mining maintenance, the cost of equipment failure and the cost savings associated with CBM.

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Appendices

Appendix A – Exception report

ESCO logo

Site name

Exception Report

29 April 2018

Generated on 30 April 2018 for:

Mine logo

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Summary of critical exceptions

Parameter	Critical Limit	Violation duration (hours)	Violation period average
85L BFan Fan NDE Vib	4 mm/s	24	6.42 mm/s
75L P5 Pump Vib	4 mm/s	15.5	4.64 mm/s
102L BFan Fan NDE Vib	4 mm/s	9	5.27 mm/s
71L FP4 Motor DE Vib	4 mm/s	8.5	4.11 mm/s
75L P4 Motor Vib	4 mm/s	6.5	5.60 mm/s
Comp3 Gbox Pin NDE Temp	65° C	4.5	67.63° C
29L P1 Pump Vib	4.5 mm/s	4.5	5.08 mm/s
75L P3 Pump DE Temp	75° C	2.5	75.94° C
75L P3 Pump Vib	4 mm/s	1.5	4.06 mm/s
100L FP3 Comp NDE Vib	4 mm/s	0.5	4.00 mm/s

Summary of warning exceptions

Parameter	Warning Limit	Violation duration (hours)	Violation period average
DK MainFan 1 Fan Vib	3 mm/s	24	3.26 mm/s
85L BFan Motor DE Vib	3 mm/s	24	3.78 mm/s
SBAC MM1 Fan NDE Vib	3 mm/s	24	3.38 mm/s
100L FP3 Motor NDE Temp	75° C	23.5	76.63° C
100L FP3 Comp DE Vib	3 mm/s	20.5	3.11 mm/s
100L FP3 Motor DE Temp	75° C	15.5	75.75° C
Comp1 Comp DE Temp	60° C	19	60.57° C
Comp1 Gbox DE Temp	55° C	14	55.70° C
75L P4 Pump Vib	3 mm/s	15.5	3.85 mm/s
115L P4 Pump DE Temp	70° C	10	70.96° C
Comp4 Gbox Thrust Temp	60° C	8	60.24° C
29L P1 Motor DE Temp	70° C	4.5	73.89° C
Comp3 Comp DE Temp	60° C	2.5	60.45° C
115L P2 Pump NDE Temp	70° C	2	70.33° C
SFP2 Motor NDE Temp	70° C	1	71.73° C

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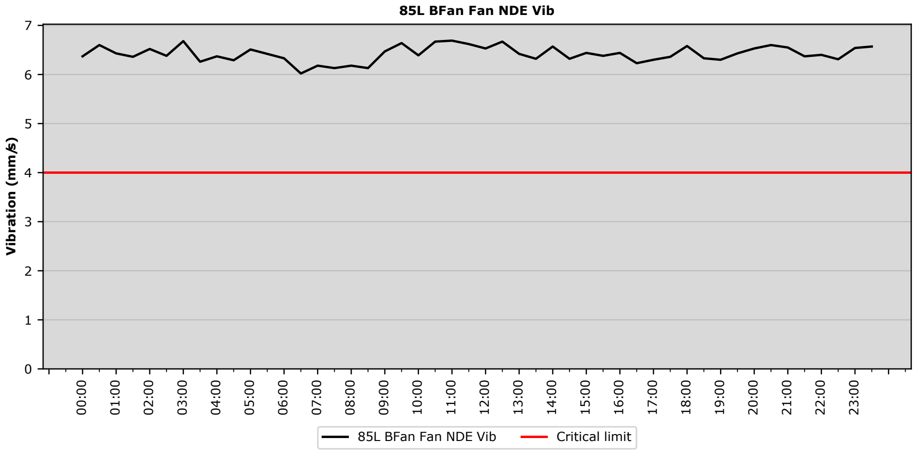
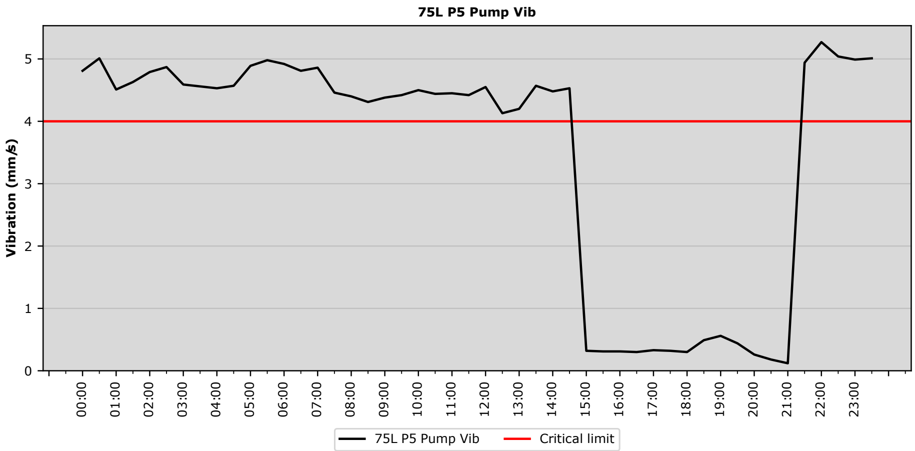
Appendix: Critical exception graphs





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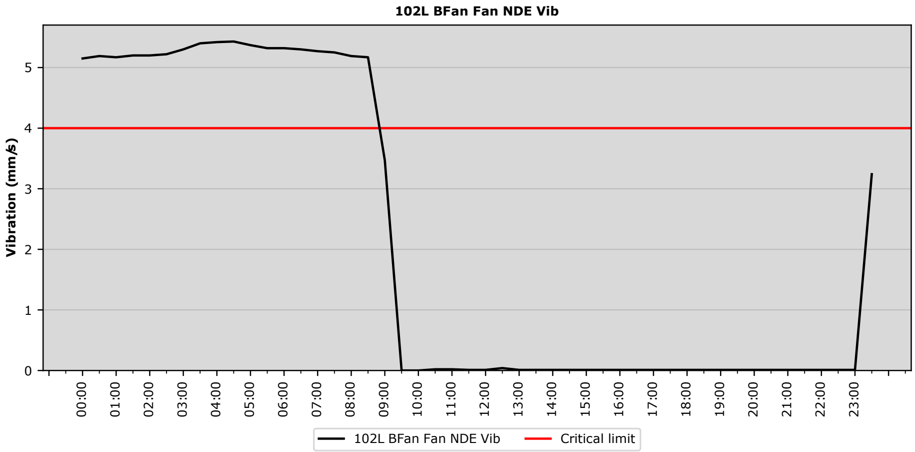

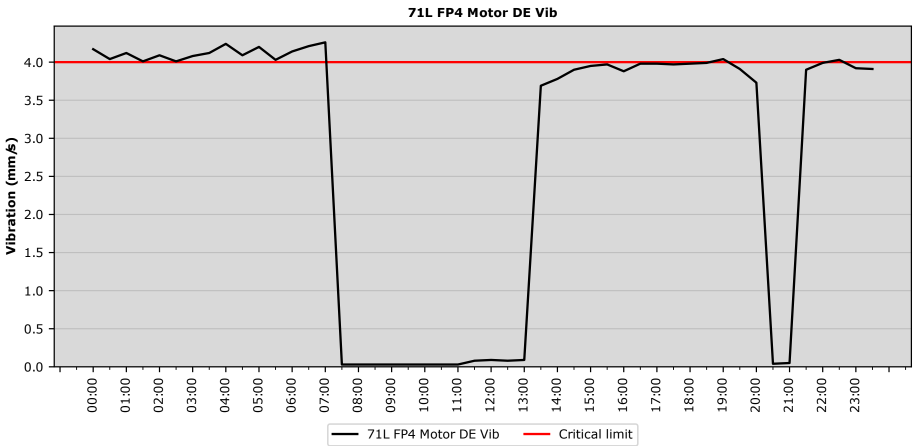

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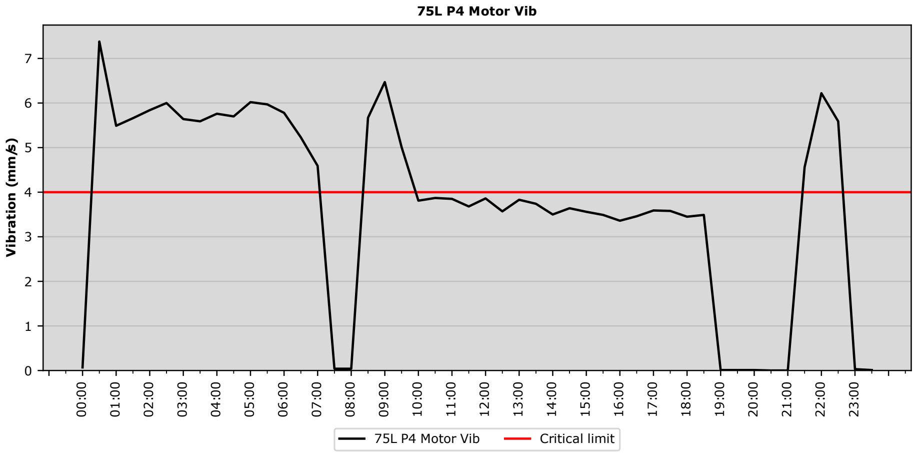

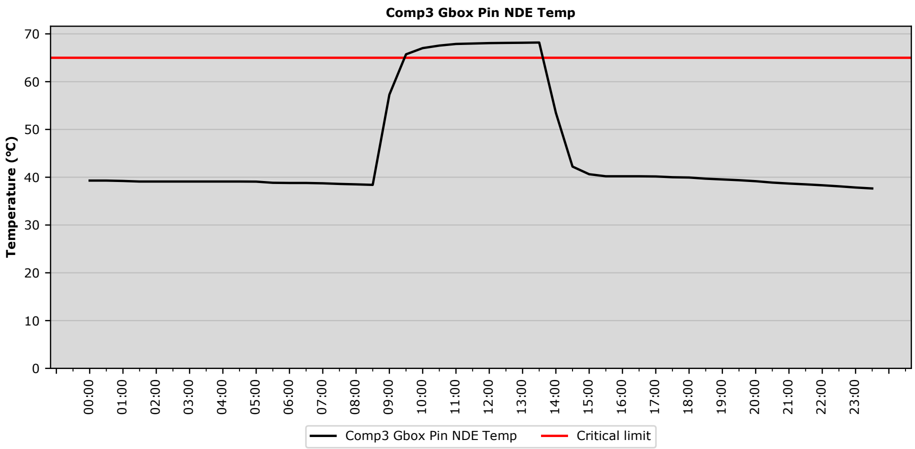

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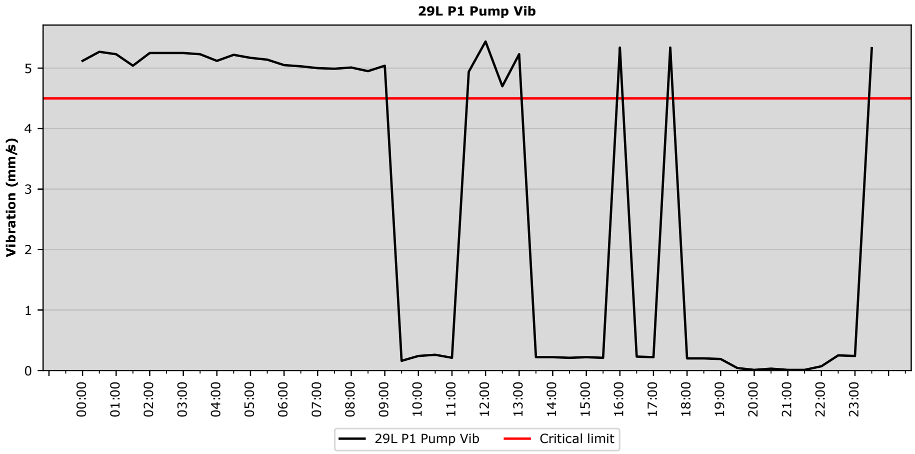

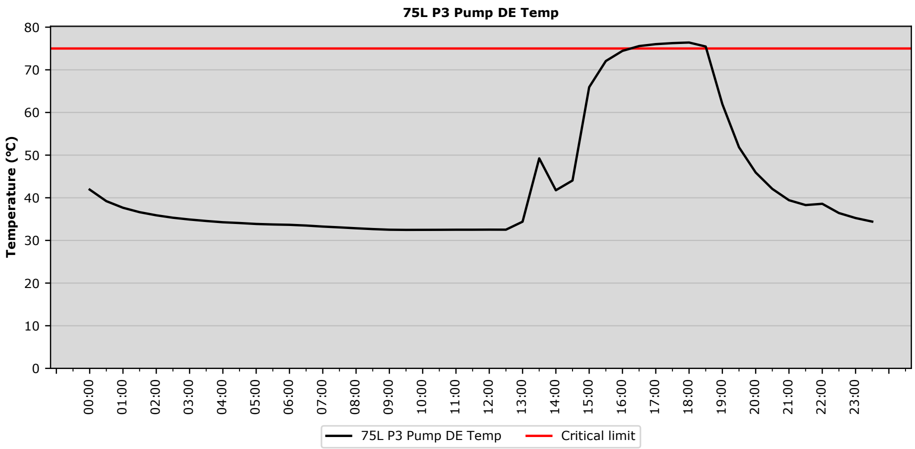

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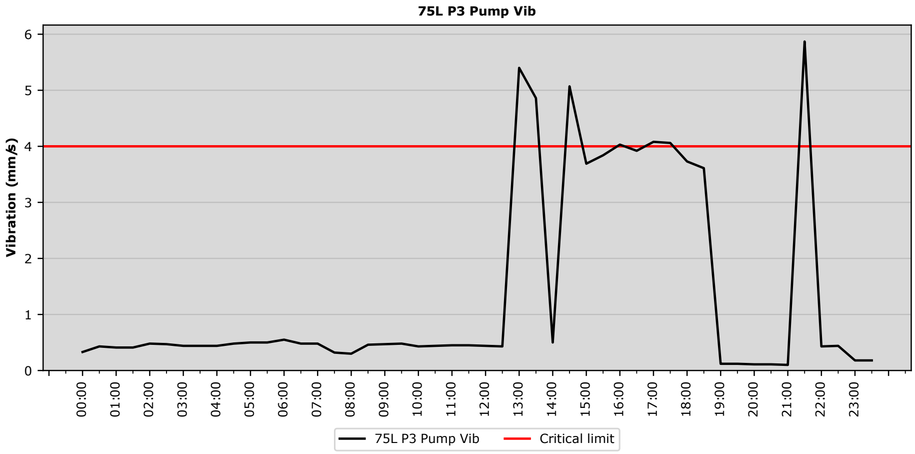

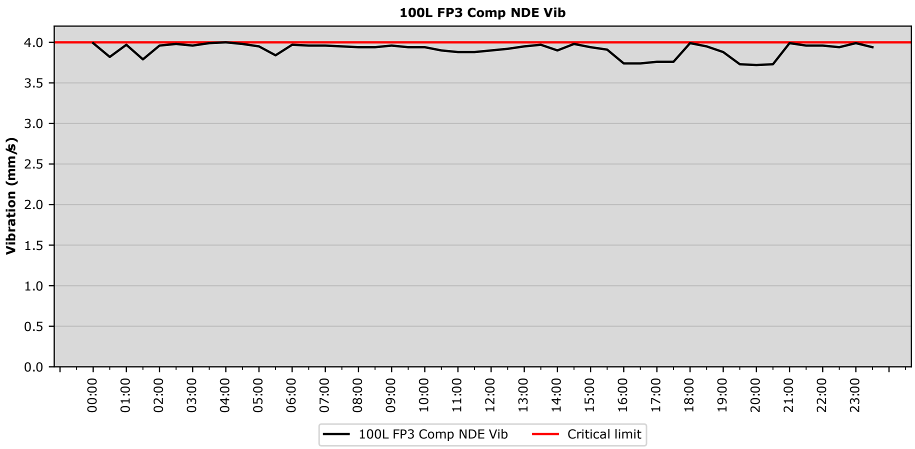

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Comments

Name:

Notes:

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Appendix B – System specific report

ESCO logo

Critical Exceptions - Pumping

Site name

03 May 2018

Generated on 04 May 2018 for:

Mine logo

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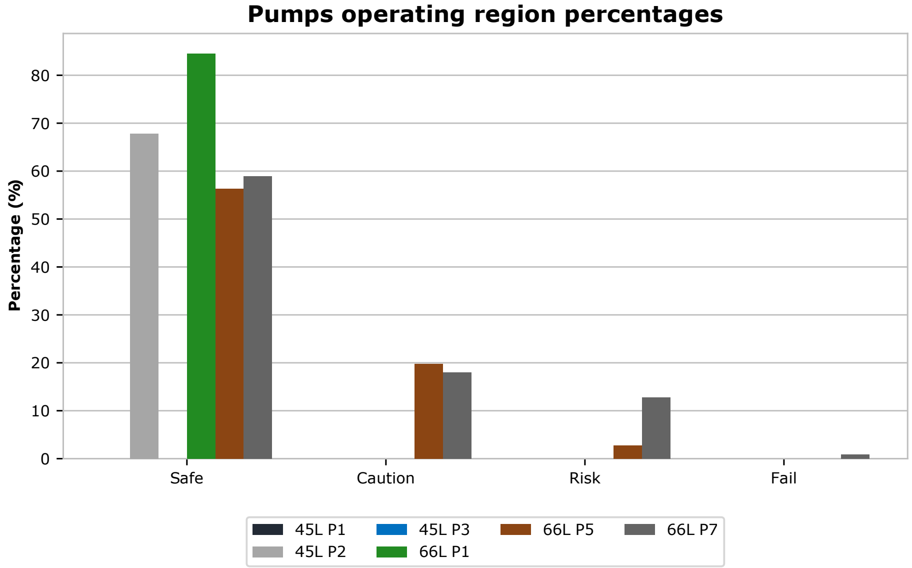
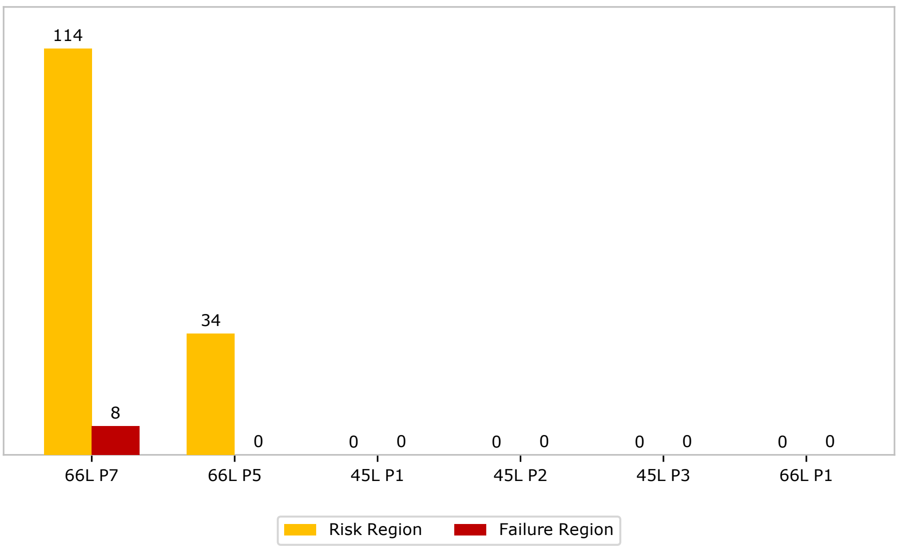
Summary of critical exceptions





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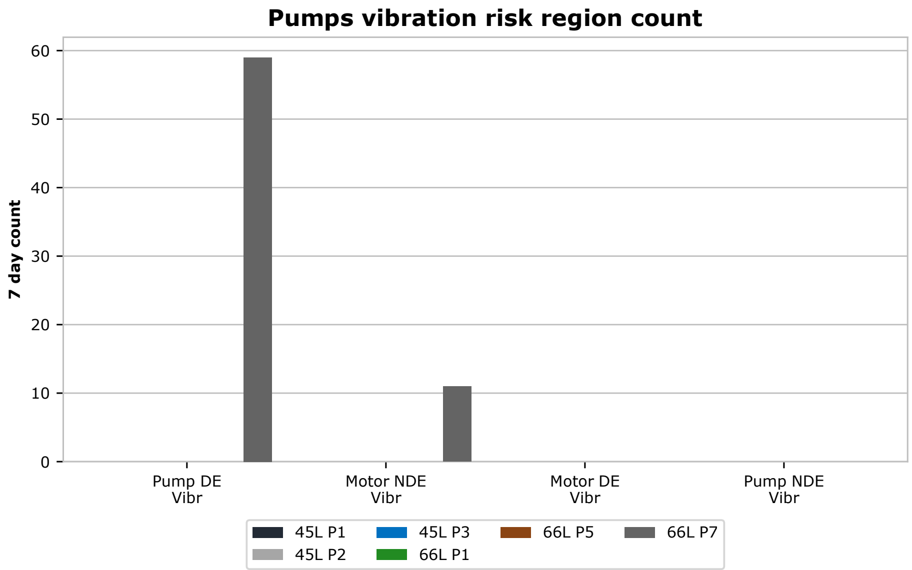

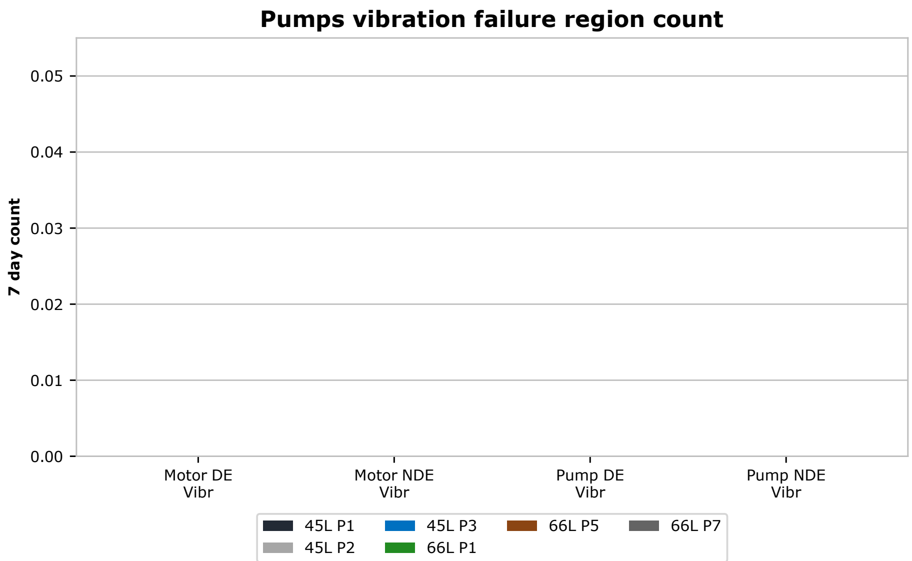

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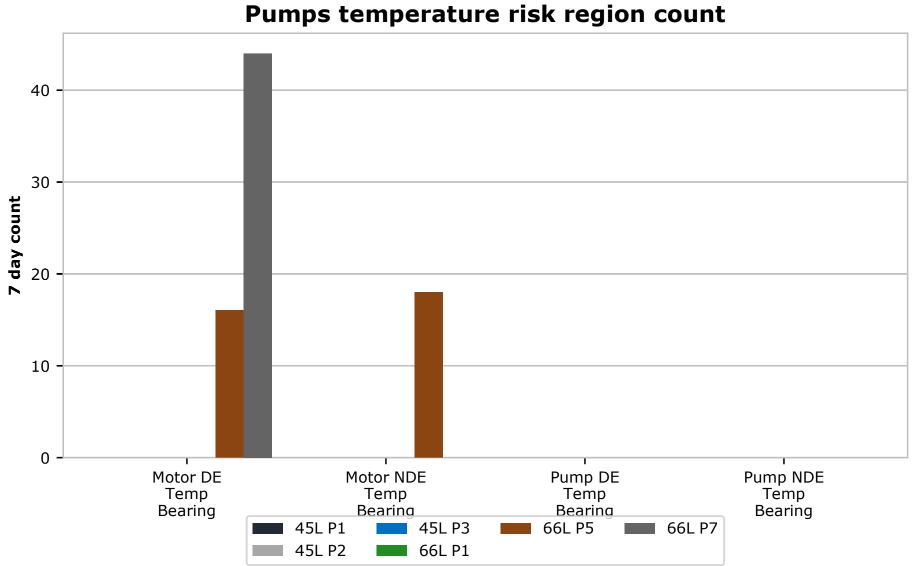

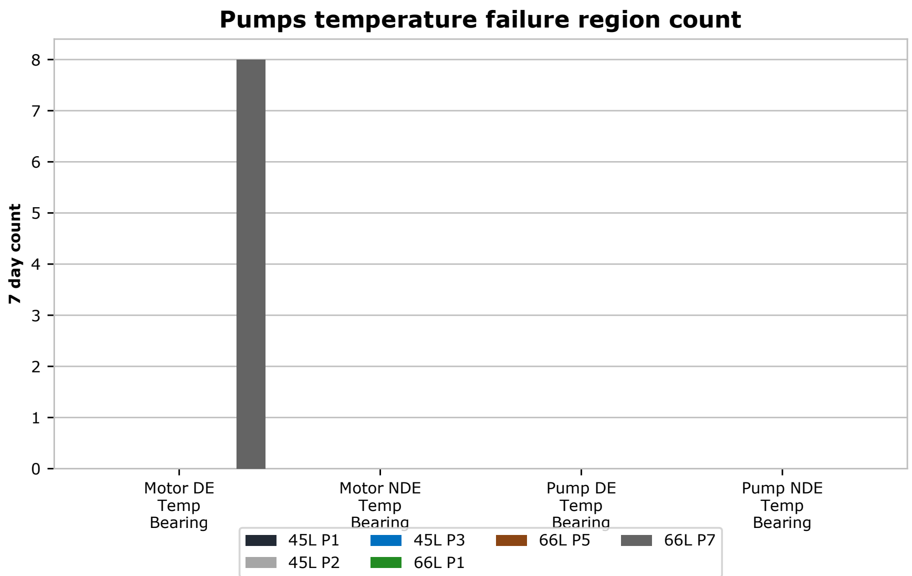

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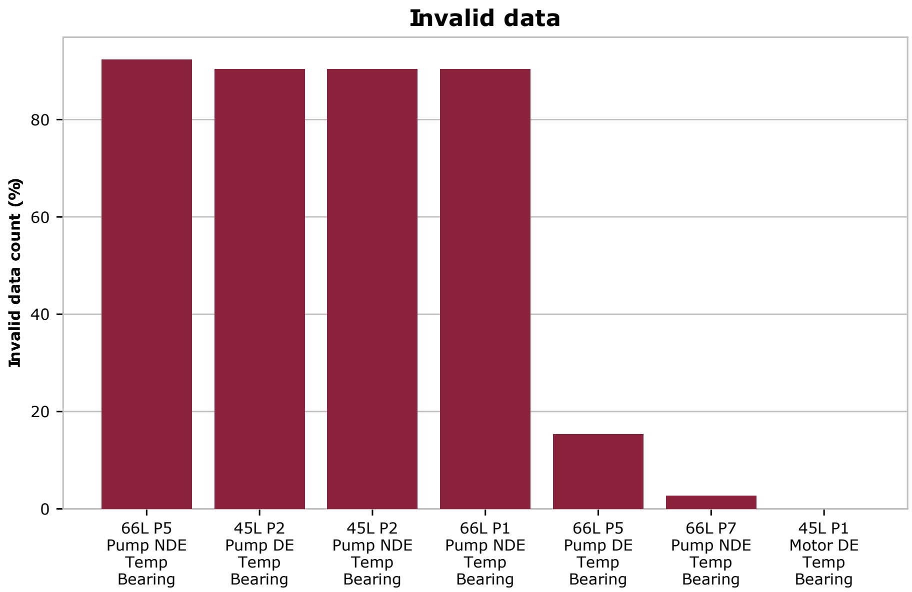

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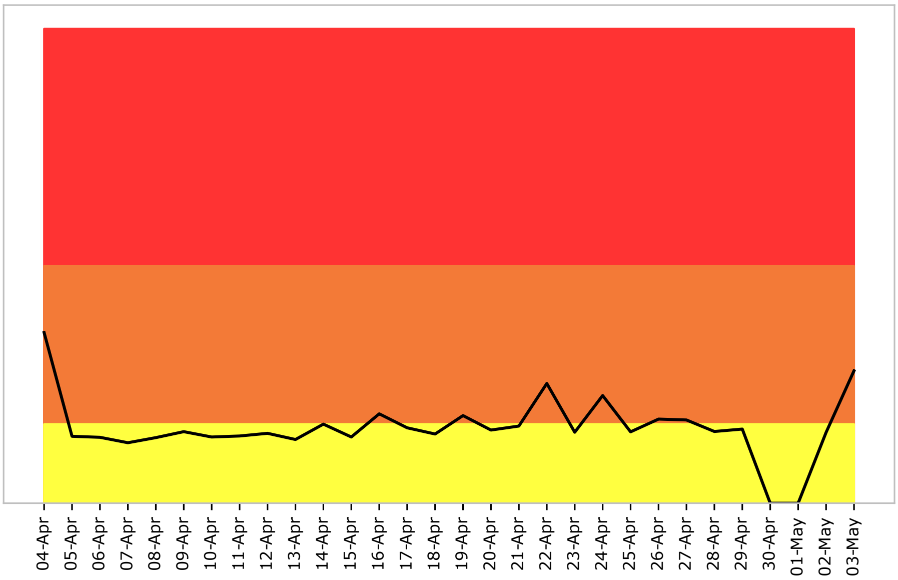
66L P5 Motor NDE Temp Bearing



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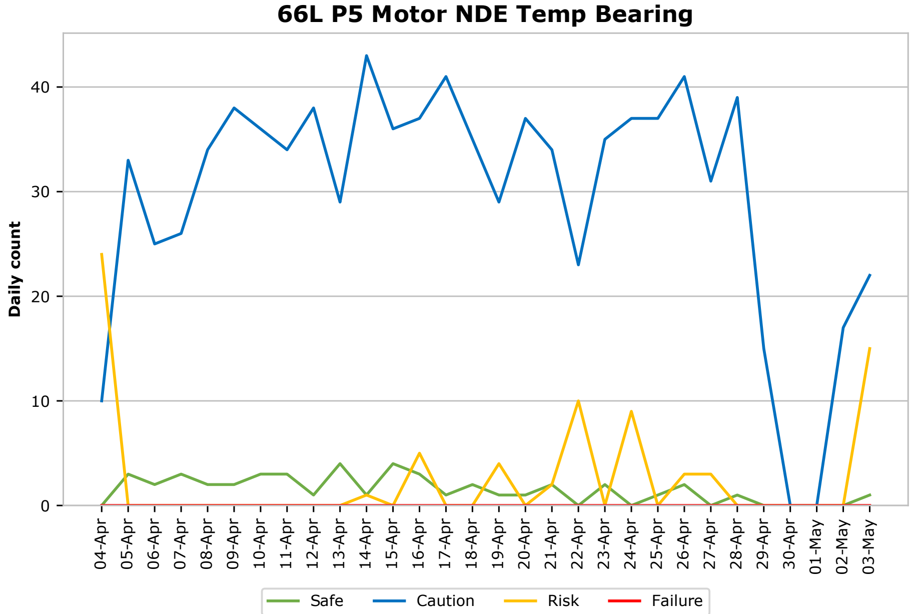

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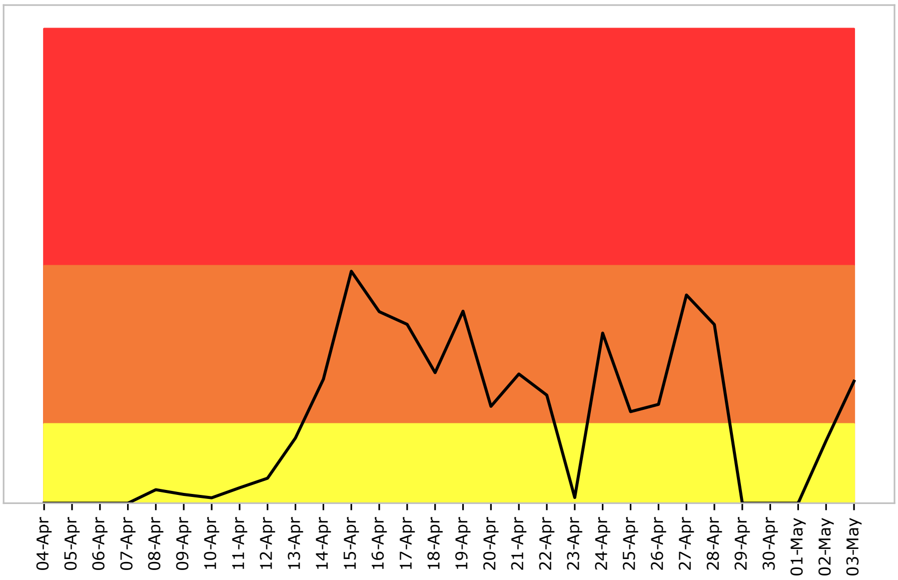
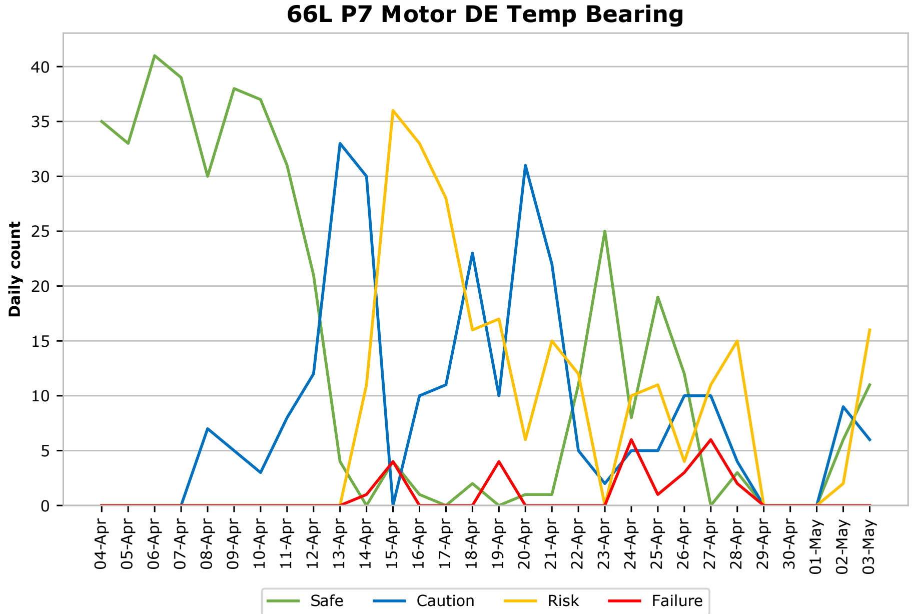
66L P7 Motor DE Temp Bearing



66L P7 Motor DE Temp Bearing



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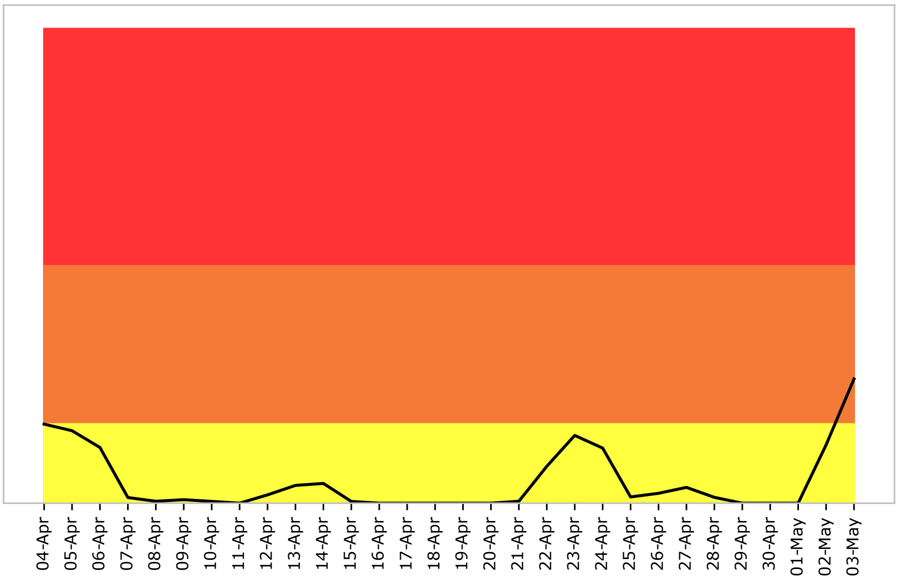
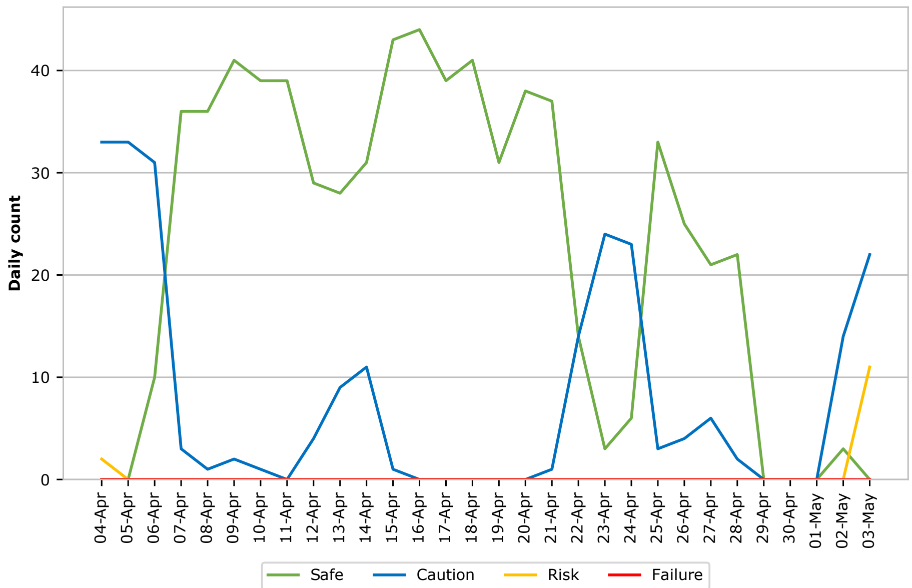
66L P7 Motor NDE Vibr



66L P7 Motor NDE Vibr



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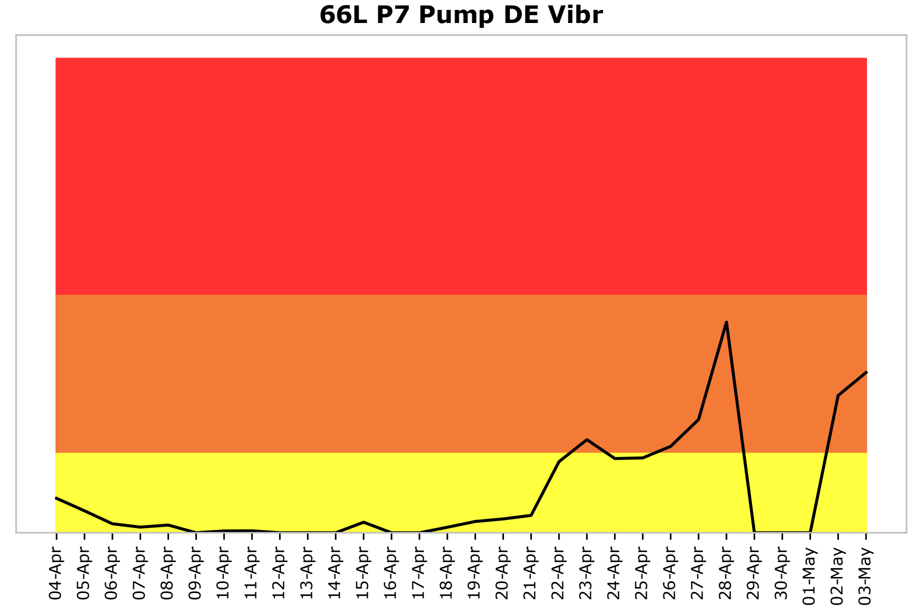

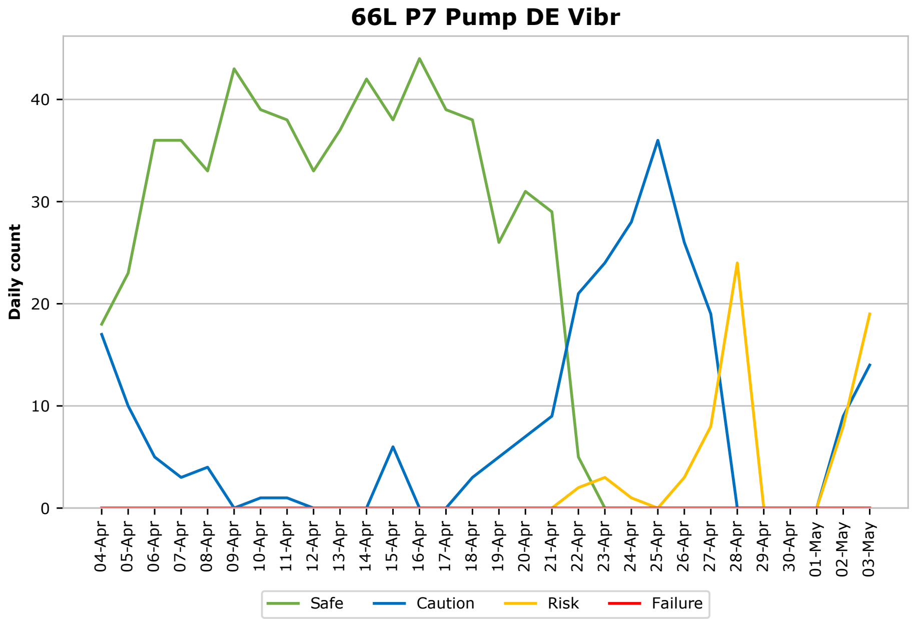

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